Examining Movement Behaviours in Preschool-Aged Children: Novel Measurement and Data Analysis Techniques

by

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Abstract

Movement behaviour patterns (e.g., more sleep, less sedentary behaviour, and more physical activity) in isolation have demonstrated benefits to preschool-aged children's development. However, the integrated nature of movement behaviours is a relatively unexplored area. This scarcity of evidence presents an opportunity to sequentially build a foundation of high-quality evidence. The overall objective of this dissertation was to systematically advance the area of movement behaviours in preschool-aged children using novel measurement and data analyses techniques.

Three manuscripts were written to address this objective. Data were collected from July-November 2018 on a sample of children aged 3-5 years and a parent. Parents/guardians were recruited from Edmonton, Canada and surrounding areas through a local division of Sportball, a program that aims to teach children fundamental sport skills through play. In total, 131 parents/guardians agreed to participate. Children's and parents' movement behaviours were measured with waist-worn ActiGraph WGT3X-BT accelerometers.

The objective of the first manuscript was to create a sleep (i.e., night and nap) classification technique. A total of 1,091,232,000 accelerometer observations in 30 Hz epochs were used to calculate 144 features (e.g., fast Fourier transformations, axis specific offset angles, kurtosis) aggregated to 1-minute epochs. Ground truth estimates of sleep were classified using visual inspection techniques. Random forest models were trained and tested using leave one subject out cross-validation, followed by temporally smoothing predictions with Hidden Markov Modeling. Additionally, a simplified prediction formula was created using 10 features with the highest mean decrease in Gini index during training of Random Forests, and temporally

smoothed with rolling median calculations. Findings demonstrated that machine learning techniques could distinguish between sleep and wake with 96% accuracy, while the simplified formula reached 94% accuracy. Though, significant differences were found between machine learning and ground truth behaviour predictions for participant-level daily summaries, whereas non-significant differences were found between the simplified formulas and ground truth predictions.

The objective of the second manuscript was to examine the relationships between accelerometer-derived movement behaviours and indicators of physical (i.e., motor skills, adiposity, and growth), cognitive (i.e., response inhibition, visual-spatial working memory, and vocabulary) and social-emotional (i.e., sociability, externalizing, internalizing, prosocial behaviour, and self-regulation [i.e., cognitive, emotional, and behavioural]) development using compositional analyses. Compositional linear regression models and compositional substitution models were conducted to examine the associations between movement behaviours and indicators of development. Findings confirmed the importance of moderate- to vigorous-intensity physical activity (MVPA) for physical development, while stationary time results were mixed for cognitive development outcomes.

The objective of the third manuscript was to examine the associations of parental movement behaviours, parent-child proximity behaviours, and proximity movement behaviours with children's movement behaviours using Bluetooth-enabled accelerometers. Child, parent, and proximity detection accelerometer files were merged and children's movement behaviour variables were categorized as no proximity (NP), proximity but mismatching movement behaviours (Close), and proximity with matching movement behaviours (Co). Compositional and non-compositional analyses were utilized to examine patterns in children's movement behaviours based on these contextual parent-child variables. Findings indicated parent-child movement behaviours were not associated, however close proximity was positively associated with children's light-intensity physical activity (LPA), and NP-MVPA was positively associated with children's MVPA.

The findings within this dissertation make important contributions to movement behaviour research in preschool-aged children. Methods were presented to accurately classify daytime and nighttime sleep in preschool-aged children. However, future studies should replicate these findings using other ground-truth estimates of sleep (e.g., polysomnography). For relationships between movement behaviours and health/developmental outcomes, findings supported evidence of a favourable association between MVPA and physical development. Additionally, the associations between stationary time and cognitive development were mixed, so future research should examine sedentary behaviours (e.g., sitting, reading) and cognitive development to explain this heterogeneity. For relationships between correlates and movement behaviours, findings indicated that parent-child close proximity was associated with children's LPA, while children's NP-MVPA was associated with higher levels of total MVPA. Future research should measure the whole family unit to better understand the dynamics of the household that are associated with children's movement behaviours. Taken together, it may be advantageous to promote independent MVPA in preschool-aged children. However, this dissertation used a cross-sectional study design from a convenience sample, so future research should test these findings with longitudinal or experimental studies in larger and more generalizable samples.

Preface

This dissertation is an original work by Nicholas Kuzik. The University of Alberta Research Ethics Board granted ethics approval to collect data (Study ID: Pro00081175) that was used to create three manuscripts. For all manuscripts I conceived and designed the study; collected, managed, analyzed, and interpreted the data; and led the writing of the manuscripts.

Chapter 3 or Manuscript 1 is being revised for submission as: Kuzik N, Spence JC, and Carson V. Machine Learning Sleep Classification in Preschoolers using Waist-Worn ActiGraphs. JC Spence and V Carson provided feedback on the study concept and design, data analyses and interpretation, and revised the manuscript critically for important intellectual content. All authors read and approved the final manuscript.

Chapter 4 or Manuscript 2 has been accepted for publication in the journal Plos One as: Kuzik N, Naylor PJ, Spence JC, and Carson V. Movement behaviours and physical, cognitive, and social-emotional development in preschool-aged children: cross-sectional associations using compositional analyses. PJ Naylor, JC Spence, and V Carson provided feedback on the study concept and design, data analyses and interpretation, and revised the manuscript critically for important intellectual content. All authors read and approved the final manuscript.

Chapter 5 or Manuscript 3 is being revised for submission as: Kuzik N, Naylor PJ, Spence JC, and Carson V. Parent-Child Movement Behaviours and Bluetooth Proximity in Preschool-Aged Children. PJ Naylor, JC Spence, and V Carson provided feedback on the study concept and design, data analyses and interpretation, and revised the manuscript critically for important intellectual content. All authors read and approved the final manuscript.

Acknowledgments

I am a firm believer that there can be no growth without adversity, but adversity alone is not sufficient stimulus—there needs to be a level of preparation or support to weather the storm, and a process of meaning making to rebuild and fortify the damage. There has been a lot of expected and unexpected adversity during this degree. The subsequent personal and professional growth over the past 5 years is a testament to the people who have prepared and supported me, as well as those that helped me with the search for meaning.

First, I would like to thank my supervisor Dr. Valerie Carson for her unwavering support and feedback. Your mentorship during these last two degrees have had a profound impact on me, and I would be lucky if even a sliver of your productivity, efficiency, and intuition will be carried with me into my future career. Further, I will always cherish the great food and company at the Carson and Carson dinners. I hope you find a future student to fill my role, and make sure you never have leftovers.

To my supervisory committee Dr John Spence and Dr PJ Naylor, I also owe a great debt of gratitude. Your career and technical guidance during this process has been tremendous, and I am incredibly grateful for the chance to collaborate with you both and hope that I can model some of your qualities in my career.

I would like to thank all the parent’s and children who participated in this research and made it possible. Sportball Edmonton for their crucial support during recruitment and data collection. As well, Amanda Ebert, Anthony Bourque, April English, Autumn Nesdoly, Brendan Wohlers, Carminda Lamboglia, Clara-Jane Blye, Evelyn Etruw, Jenna Davie, Kelsey Wright, Kevin Arkko, Madison Predy, Rebecca Rubliak, Ria Duddridge, Stephen Hunter, and Tyler Ekeli for their assistance during the motor development data collection.

Thank you very much to my BEL lab mates past and present who listened to countless half formed thoughts and statistics rantings, participated in all the BEAR Club meetings, went through all the practice presentations, or played lots of basketball with me (okay maybe that one is just Stephen). I cannot express enough how fortunate I am to have such an amazing lab space. I hope to have a lifelong list of collaborators and friends from the BEL lab!

To all my friends and family, I surely would have fallen without your constant support. I should note that was a metaphor because in reality I have substantial balance and can only recall 2.5 sober instances of falling as an adult. Specifically, to my family—thank you for creating an environment that fostered hard-work and curiosity. I will never claim to be smart, but I do feel I am very hard working and curious, so thank you. To Ula, even though I met you near the finish line, your support and conversations since we met have been crucial. Everyone knows the finish line can be the hardest part, but you gave me the strength to keep pushing. I am so excited to start a new chapter with you and Indy (for context, Indy is a dog and objectively a very good boy). I would list out all the great friends I have made over this degree but there is not enough room, just know that I want to thank you all for keeping me happy and sane!

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1 Introduction

1.1 General introduction

Human movement can be conceptualized as occurring on a spectrum of movement intensity, and can be categorized into three mutually exclusive behaviours—sleep, sedentary behaviour, and physical activity, which are collectively referred to as movement behaviours (see Figure 1.1). Traditionally, these behaviours have been studied in isolation but recent research provides compelling evidence that the integrated relationship of movement behaviours should be considered (Chastin, Palarea-Albaladejo, Dontje, & Skelton, 2015; Pedišić, 2014; Pedišić, Dumuid, & Olds, 2017). In line with this evidence, Canada has recently released *Canadian 24-Hour Movement Guidelines for Early Years Children (0-4 years): An Integration of Physical Activity, Sedentary Behaviour, and Sleep (Tremblay et al., 2017c)*. The initial formation of movement behaviour habits during the early years makes it an especially important age to study (Goldfield, Harvey, Grattan, & Adamo, 2012). Additionally, this age range is a particularly sensitive period for a number of health related developmental indicator trajectories (e.g., physical, cognitive, and social-emotional development) (Berk, 2013). Therefore, it is alarming that only 13% of Canadian preschool-aged children are meeting the newly developed 24-Hour Movement Guidelines (i.e., 180 minutes/day TPA including 60 minutes/day MVPA, <1 hour/day screen time, and 10-13 hours/day of sleep) (Chaput et al., 2017a). Despite the importance of this age range for movement behaviours, and development, a systematic review conducted by our group found no studies examining the relationships between all movement behaviours and developmental indicators in early years children (Kuzik et al., 2017).

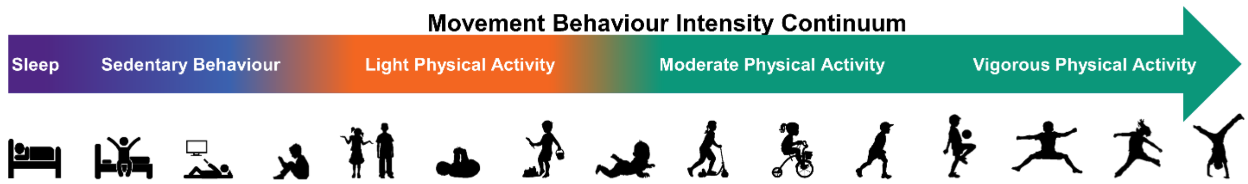

Figure 1.1: Movement Behaviour Intensity Continuum

The dearth of evidence in this area presents a timely opportunity to create a foundation of evidence, which if conducted appropriately could lead to a high-quality evidence base. The framework for Viable Integrative Research in Time-Use Epidemiology (VIRTUE) is one tool that could guide a systematic and sequential process to follow in the early stages of movement behaviour research (Pedišić et al., 2017). More specifically, the VIRTUE Framework proposes the following sequence of research: 1) Methodological research in time-use epidemiology (i.e., measurement, developing surveillance, and data processing and analysis), 2) Outcomes of health-related time-use compositions, 3) Time-use compositions (i.e., optimal balance, prevalence, and trends), 4) Determinants and correlates of optimal time-use, and 5) Time-use interventions (See Figure 1.2).

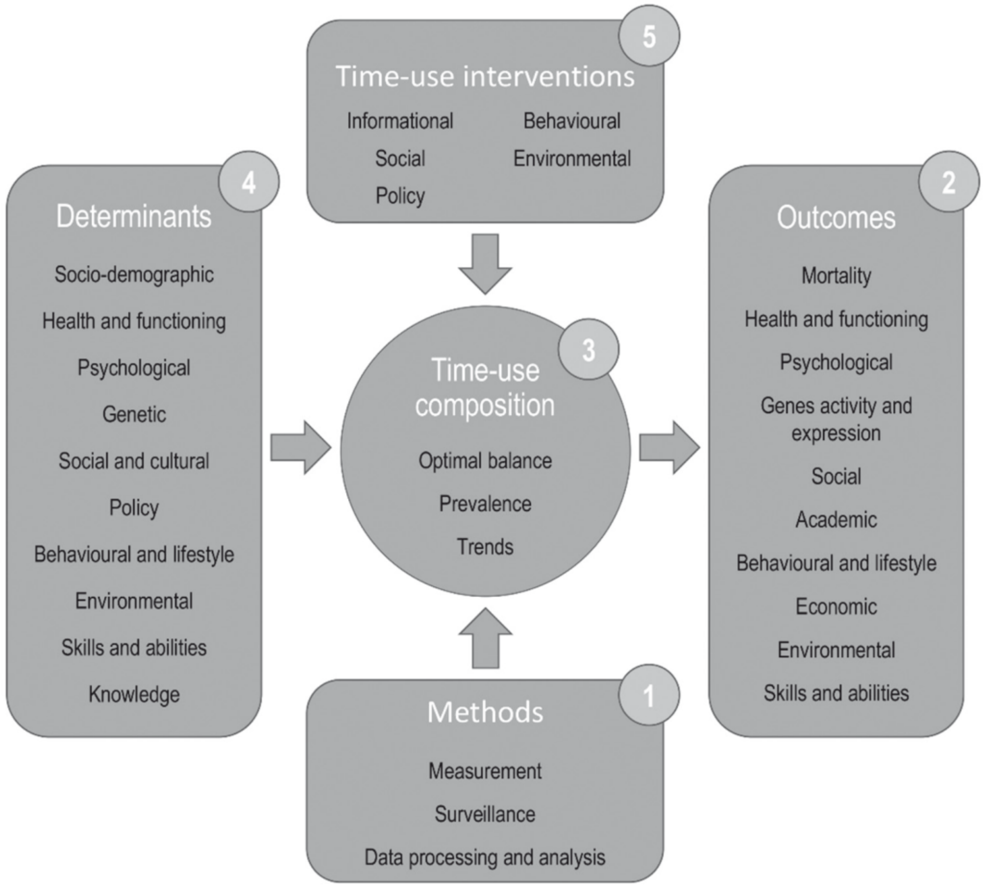

Figure 1.2: VIRTUE Framework. Source: Pedišić et al (2017).

This dissertation consists of three manuscripts in preschool-aged children that combined will address the main topics outlined in stages 1, 2, 3, and 4 within the VIRTUE framework. The overall goal of this research is to systematically advance the area of movement behaviours in preschool-aged children using novel measurement and data analyses techniques.

1.2 Objectives

The specific objectives of this research are:

Objective 1: Create a sleep classification technique for waist-worn ActiGraph accelerometers in preschool-aged children using a feature extraction and machine learning process.

Objective 2: Examine the relations between accelerometer-derived movement behaviours and indicators of physical, cognitive, and social-emotional development using compositional analyses in a sample of preschool-aged children.

Objective 3: Determine the prevalence of movement behaviours in preschool-aged children using accelerometers.

Objective 4: Examine the associations of parental movement behaviours and parent-child proximity with preschool-aged children's movement behaviours using Bluetooth-enabled ActiGraph accelerometers and compositional analyses.

1.3 Definitions of key terms

1.3.1 Determinant/Correlate

Correlates and determinants are factors that are associated with an outcome or multiple outcomes of interest. Within the area of behavioural epidemiology, factors that are associated with behaviours are generally referred to as determinants and correlates (Bauman, Sallis, Dzewaltowski, & Owen, 2002). A key distinction between correlates and determinants, is determinants are able to establish temporality, which is a necessary, or sufficient, criterion to determine if an association is causal (Bauman et al., 2002). Therefore, correlates cannot establish cause-and-effect relationships, but they can generate hypotheses for future research. Correlates and determinants are often conceptualized through a multilevel ecological approach to conceptualize the causal web of influence exerted on behaviours (Sallis, Owen, & Fisher, 2015).

1.3.2 Early years children

Early years children is a classification that can be subdivided into the main age categories of: infants, toddlers, and preschool-aged children. The age groupings are descriptive (i.e., infant is

Latin for unable to speak, toddler refers to the beginning of unsteady walking or toddling, and preschool-aged refers to the age before starting formal schooling). Though the main focus of this dissertation is on preschool-aged children (3-5 years), research involving younger and older age groups is discussed in the literature review to either bridge the gaps or highlight future research needs.

1.3.3 Accelerometer

Simply put an accelerometer measures movement by recording accelerations produced by a moving body. Modern accelerometers can measure movement in the vertical (up and down), frontal (side to side), and sagittal (forward and backward) axes of motion (Chen & Bassett, 2005). Additionally, a combination of these three axes can be used to calculate the vector magnitude ($Vector\ magnitude = \sqrt{vertical\ axis^2 + sagittal\ axis^2 + horizontal\ axis^2}$). The most common accelerometer used to measure movement behaviours in early years children is the ActiGraph (Cliff et al., 2009; Migueles et al., 2017). Thus, the ActiGraph WGT3X-BT accelerometer is used in the manuscripts outlined in this dissertation.

1.3.4 Sleep

A common definition of sleep is a loss of conscious awareness (Brown, Basheer, McKenna, Strecker, & McCarley, 2012). This dissertation will focus on sleep quantity or duration, which is often defined as the total amount of sleep in a 24-hour period and can further be broke down into daytime and nighttime sleep (Galland et al., 2012). During a 24-hour day, children aged 0-5 years generally sleep in shorter daytime (i.e., napping) bouts and longer nighttime bouts. Sleep is measured with accelerometers in this dissertation research and therefore is based on a movement standpoint. Specifically, the inherent time (e.g., mean acceleration during epoch), frequency (e.g., number of accelerations greater than 0 during epoch), and angular (e.g., accelerometer angle relative to y-axis) properties of accelerometer data will be extracted and used to predict the probability of sleep.

1.3.5 Sedentary behaviour

Sedentary behaviour is defined as any waking behaviour with low energy expenditure (i.e., ≤1.5 metabolic equivalents) occurring in a sitting, reclining, or lying posture (Tremblay et al., 2017a), while sedentary time refers to the time spent in sedentary behaviours (Tremblay et al., 2017a). Recently, when defining sedentary behaviour and related terms, Tremblay et al (2017) proposed the term stationary behaviour, which refers to any waking behaviour devoid of ambulation, regardless of energy expenditure or posture (Tremblay et al., 2017a) and stationary time, which refers to the time spent in stationary behaviours (Tremblay et al., 2017). While some accelerometers are able to detect posture (e.g., AcitivPal), the ActiGraph is generally used to detect only motion, which would give an estimate of stationary time. Thus, stationary time will be the sedentary-related behaviour of interest in this dissertation.

1.3.6 Physical activity

Physical activity is typically defined as any bodily movement produced by skeletal muscles that results in energy expenditure above the resting metabolic rate (Caspersen, Powell, & Christenson, 1985). In the classic definition of physical activity, Caspersen, Powell, & Christensen (1985) consider any movement as physical activity, thus sedentary behaviour and even sleep are considered physical activities (e.g., *"[t]he energy expenditure due to physical activity during sleep would, of course, be small*"). However, within this dissertation, physical activity will be considered any movement measured by accelerometers that is not already considered stationary time, sleep, or non-wear time. Categories of physical activity will consist of light-intensity physical activity (LPA) and moderate- to vigorous-intensity physical activity (MVPA) which will further be defined in Section 2.2.1.2.4.

1.3.7 Movement behaviours

Movement behaviours is an umbrella term that encapsulates behaviours occurring on an intensity spectrum from low intensity (e.g., sleep, stationary time) to high intensity (e.g., moderate-to-vigorous physical activity). Conceptually different classifications of movement behaviours are possible (e.g., energy expenditure, posture). Specific to this dissertation, movement behaviours will be classified from a movement perspective using ActiGraph accelerometers. A movement perspective for classifying movement behaviours can be considered a proxy for energy expenditure based on intensity of movement (i.e., stationary time and physical activity), and a proxy for sleep detection based on the characteristics of movement (e.g., time, frequency, and angular characteristics). Based on this classification system, three broad categories of movement behaviours are operationalized to study (see Section 2.2.1.2.4): sleep, stationary time, and physical activity. However, within the literature review different conceptualizations of movement behaviours will be discussed (e.g., sedentary time, sedentary behaviour).

1.3.8 Ground truth

Conceptually, ground truth can be thought of as a "*term relative to the knowledge of the truth concerning a specific question. It is the ideal expected result*"(Lemoigne, 2008). Whereas a gold standard would be the absolute representation of the ground truth. Practically, ground truth measurements are observations intended to best represent the actual behaviour of interest. For instance, ground truth measurements of movement behaviours should use methods considered true gold-standards (e.g., polysomnography, in-room calorimetry), or valid and feasible alternatives in field-based studies (e.g., direct observation, visually inspected accelerometer data).

1.3.9 <u>Compositional data analysis</u>

Compositional data are data with "*strictly positive components that carry relative information" (Pawlowsky-Glahn, Egozcue, & Tolosana-Delgado, 2015)*. When the relative information of data is examined, as opposed to the absolute information of data, this data is meaningfully interpreted as a proportion of a whole. For example, individual movement behaviours can make up a proportion of a whole 24-hour period. Thus, all relevant information in movement behaviour durations exists as ratios between individual movement behaviours. A key feature of compositional data analyses is a specific transformation of the data, which overcomes collinearity issues of traditional statistical methods when analyzing proportions. Therefore, this method is appropriate for analyzing mutually exclusive movement behaviour data. More information on compositional data analysis can be found in section 2.2.2.

1.4 References

Bauman, A. E., Sallis, J. F., Dzewaltowski, D. A., & Owen, N. (2002). Toward a better understanding of the influences on physical activity: The role of determinants, correlates, causal variables, mediators, moderators, and confounders. *American Journal of Preventive Medicine, 23*(2, Supplement 1), 5-14. doi:https://doi.org/10.1016/S0749-3797(02)00469-5

Berk, L. E. (2013). *Development through the lifespan* (6 ed.). Boston, MA: Pearson.

Caspersen, C. J., Powell, K. E., & Christenson, G. M. (1985). Physical activity, exercise, and physical fitness: Definitions and distinctions for health-related research. *Public Health Reports, 100*(2), 126.

Chaput, J.-P., Colley, R. C., Janssen, I., Carson, V., Roberts, K. C., Aubert, S., & Tremblay, M. (2017a). Proportion of preschool-aged children meeting the Canadian 24-Hour Movement Guidelines for the Early Years and associations with adiposity: Results from the Canadian Health Measures Survey. *BMC Public Health, 17*(5), 829.

Chastin, S. F., Palarea-Albaladejo, J., Dontje, M. L., & Skelton, D. A. (2015). Combined effects of time spent in physical activity, sedentary behaviors and sleep on obesity and cardio-metabolic health markers: A novel compositional data analysis approach. *PLOS ONE, 10*(10), e0139984. doi:10.1371/journal.pone.0139984

Goldfield, G. S., Harvey, A., Grattan, K., & Adamo, K. B. (2012). Physical activity promotion in the preschool years: A critical period to intervene. *International Journal of Environmental Research and Public Health, 9*(4), 1326-1342. doi:10.3390/ijerph9041326

Kuzik, N., Poitras, V. J., Tremblay, M. S., Lee, E.-Y., Hunter, S., & Carson, V. (2017). Systematic review of the relationships between combinations of movement behaviours and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 849.

Lemoigne, Y. (2008). Molecular imaging computer reconstruction and practice. In A. Caner (Ed.). Dordrecht ;: Springer Science + Business Media B.V.

Pawlowsky-Glahn, V., Egozcue, J. J., & Tolosana-Delgado, R. (2015). *Modeling and analysis of compositional data*: John Wiley & Sons.

Pedišić, Ž. (2014). Measurement issues and poor adjustments for physical activity and sleep undermine sedentary behaviour research - the focus should shift to the balance between sleep, sedentary behaviour, standing and activity. *Kinesiology: International journal of fundamental and applied kinesiology, 46*(1), 135-146.

Pedišić, Ž., Dumuid, D., & Olds, T. (2017). Integrating sleep, sedentary behaviour, and physical activity research in the emerging field of time-use epidemiology: Definitions, concepts, statistical methods, theoretical framework, and future directions. *Kinesiology: International journal of fundamental and applied kinesiology, 49*(2), 10-11.

Sallis, J. F., Owen, N., & Fisher, E. (2015). *Ecological models of health behavior* (5 ed.). San Francisco: Jossey-Bass.

Tremblay, M. S., Aubert, S., Barnes, J. D., Saunders, T. J., Carson, V., Latimer-Cheung, A. E., . . . on behalf of, S. T. C. P. P. (2017a). Sedentary Behavior Research Network (SBRN) – Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 75. doi:10.1186/s12966-017-0525-8

Tremblay, M. S., Chaput, J.-P., Adamo, K. B., Aubert, S., Barnes, J. D., Choquette, L., . . . Carson, V. (2017c). Canadian 24-hour movement guidelines for the early years (0–4 years): An integration of physical activity, sedentary behaviour, and sleep. *BMC Public Health, 17*(5), 874.

2 Review of Literature

2.1 VIRTUE framework

Low levels of sleep, high levels of sedentary behaviour, and low levels of physical activity in isolation are risk factors for a range of health indicators in children (Carson et al., 2016; Carson et al., 2017c; Chaput et al., 2016; Chaput et al., 2017c; Poitras et al., 2016; Poitras et al., 2017). However, recent research suggests that these behaviours are not independent risk factors and are instead integrated (Carson, Tremblay, & Chastin, 2017d; Chaput, Carson, Gray, & Tremblay, 2014; Chastin et al., 2015; Dumuid et al., 2017). Traction for this concept has been demonstrated through public health guidelines (Tremblay, 2019), novel applications of analytical techniques for movement behaviour research (Carson et al., 2017d; Dumuid et al., 2017), and most recently a proposed framework to help guide this area of research—the Viable Integrative Research in Time-Use Epidemiology (VIRTUE) (Pedišić et al., 2017). The VIRTUE framework is based on the social-ecological models (Bronfenbrenner, 1979), Activity Balance Model (Pedišić, 2014), and the behavioural epidemiology framework (Sallis, Owen, & Fotheringham, 2000). The VIRTUE framework and the behavioural epidemiology framework are very similar, as authors of the VIRTUE framework consider time-use epidemiology to be encompassed by behavioural epidemiology (Pedišić et al., 2017). The VIRTUE framework was developed specifically for the time component of behaviours occurring over the day. Pedišić et al. (2017) propose five research categories within the VIRTUE framework to adequately understand the causes, consequences, ideal distributions, current prevalence and trends of movement behaviours, and how and when to intervene to promote healthy movement behaviour compositions. Ideally research should progress sequentially through the following five research categories: 1) methodological research in time-use epidemiology (methods), 2) outcomes of health-related time use compositions (outcomes), 3) optimal balance, prevalence, and trends of time-use compositions (time-use compositions), 4) correlates and determinants of optimal time-use (determinants and correlates), and 5) time-use interventions (interventions) (See Figure 2.1).

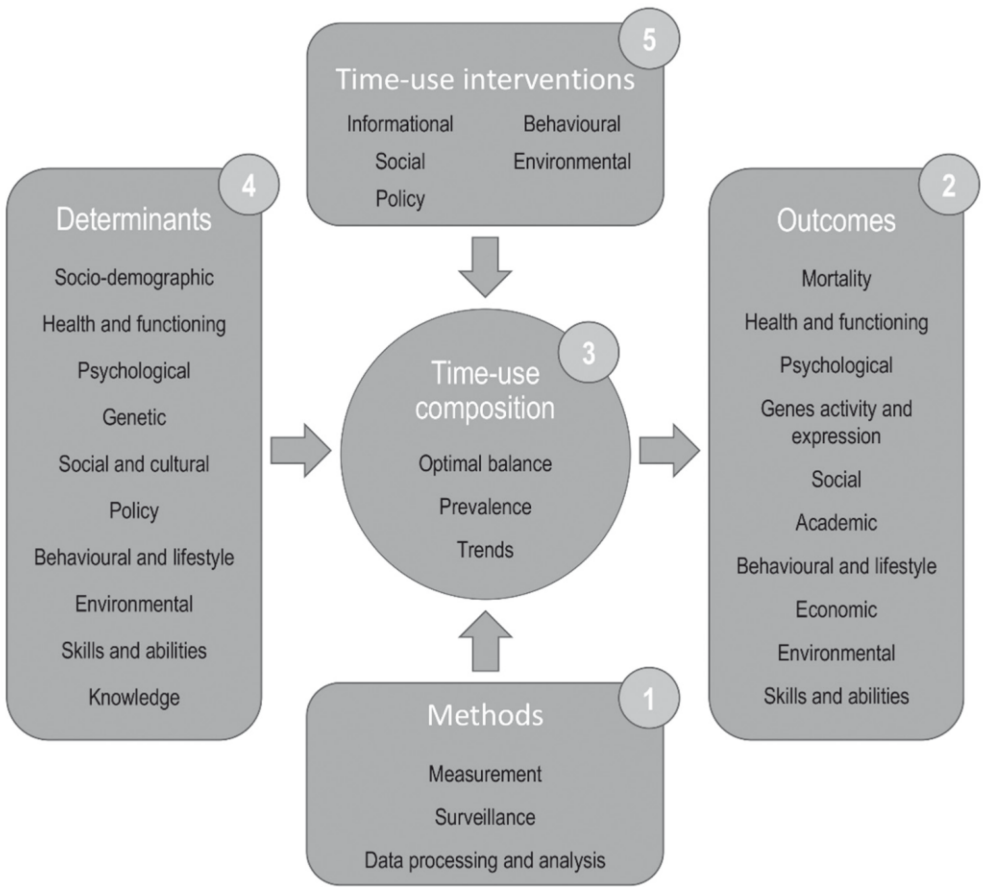

Figure 2.1: VIRTUE Framework. Source: Pedišić et al (2017).

2.1.1 <u>Research category one: Methods</u>

Within the methods research category of the VIRTUE framework, three main topics are addressed for movement behaviour research: measurement, surveillance, as well as data processing and analysis. Measurement is intuitively a first step, since without the ability to measure a movement behaviour the other stages would not be possible. Furthermore, without accurate measures of a movement behaviour, incorrect conclusions may be made in the other stages. Specific research recommendations put forth for measurement include: 1) creating or improving tools for measuring movement behaviours; and 2) using compositional data analysis to evaluate the psychometric properties of movement behaviour measurement tools. For surveillance, Pedišić et al. (2017) propose that surveillance systems (e.g., National Health and Nutrition Examination Survey [NHANES], Canadian Health Measures Survey [CHMS]) should include input from time-use epidemiologists to ensure: 1) relevant health outcomes and movement behaviours are measured; and 2) harmonization of between-study and cross-country data collection and processing protocols. Lastly, it is argued that data processing and analyses must occur via compositional data analyses. Manuscript 1 in this dissertation will broadly address the measurement topic of the methods research category.

2.1.2 Research category two: Outcomes

Within the VIRTUE framework it is stressed that health outcomes or indicators are considered with the definition of complete physical, mental, and social well-being (World Health Organization, 1948). For this reason, it is recommended that compositional data analyses are used to determine the relationships between movement behaviour compositions and a variety of biologically, psychologically, and/or socially relevant health indicators. No specific main topics are proposed for this research category but research recommendations put forth by Pedišić et al. (2017) are to determine: 1) the relationships between overall and individual movement behaviours and health indicators, including dose-response relationships; 2) the effects of substituting one movement behaviour for another (e.g., change in health indicator when 10 minutes of stationary time are substituted for 10 minutes of MVPA); and 3) the mechanisms explaining the relationships mentioned in 1) and 2) above. Manuscript 2 will address specific research recommendation 1) and 2) of the outcome research category, specifically for physical, cognitive, and social-emotional development health or developmental indicators.

2.1.3 <u>Research category three: Time-use compositions</u>

The main topics addressed in the VIRTUE framework in relation to movement behaviour compositions are optimal balances, prevalence, and trends. For optimal balances of movement behaviours, the ideal composition should demonstrate relationships with health outcomes or indicators as discussed in Section 2.1.2. This means that an optimal balance of movement behaviours must be optimal across many or all relevant health indicators. A hypothetical benchmark can then be set for an optimal balance of movement behaviours within a population of interest—though, this should also be balanced in terms of being sustainable and achievable over long periods of time to become habitual and produce desired changes. Setting a benchmark for the optimal balance of movement behaviours in a specific population could then be followed by research determining the current balance of movement behaviours in that population. Determining the prevalence of movement behaviours in a sample of the population would allow researchers to estimate if public health initiatives and interventions are needed to alter the current movement behaviours towards a hypothetical optimum level. Lastly, determining the trends of movement behaviour combinations will allow researchers to estimate the effect of public health initiatives and interventions to determine what was effective and if different strategies are needed. Specific research recommendations put forth by Pedišić et al. (2017) included: 1) using compositional analyses to determine the average time spent in each movement behaviour; 2) finding the ideal balance of movement behaviours for health; 3) determining the estimated population prevalence of meeting the ideal balance of movement behaviours; 4) identifying prevalent patterns of unhealthy movement behaviour compositions (e.g., low sleep, low stationary time, high physical activity); and 5) tracking trends in movement behaviours at a population-level over time. Manuscripts 2 and 3 will address the prevalence main topic and specific research recommendation 1) of the time-use compositions research category.

*2.1.4 **Research category four: Determinants and correlates***

Knowing determinants or correlates of movement behaviours means that targets can be identified for future interventions, as well groups with the highest risk of sub-optimal movement behaviour compositions can be identified for targeted interventions. However, most research in this area to date has looked at movement behaviours in isolation. So, taking an integrated approach would allow researchers to understand how determinants and correlates holistically influence movement behaviours. This would overcome traditional approaches where determinants or correlates are identified that influence movement behaviours in isolation without knowledge of the influence on the other movement behaviours. No specific main topics are proposed for this research category but specific research recommendations put forth by Pedišić et al. (2017) include identifying determinants or correlates of: 1) ideal combinations and individual movement behaviours, and 2) patterns of unhealthy movement behaviour compositions (e.g., low sleep, low stationary time, high physical activity). Manuscript 3 will address specific research recommendation 1) of the determinants and correlates research category.

*2.1.5 **Research category five: Interventions***

Time-use interventions are the last stage of the VIRTUE framework, since the previous stages are meant to guide the creation of meaningful interventions. In such, Pedišić et al. (2017) again stress the compositional nature of movement behaviours are considered when targeting one or more movement behaviours. No specific main topics are proposed for the research category but specific research recommendations put forth by Pedišić et al. (2017) include creating interventions aimed at: 1) altering two or more movement behaviours, while keeping the non-intervened movement behaviours constant or 2) altering all movement behaviours simultaneously. No manuscripts in this dissertation address this research category; however, findings from this work may help guide future interventions.

2.2 Methodological research in time-use epidemiology

2.2.1 Measuring movement behaviours

Many techniques and tools exist that can measure isolated movement behaviours during a 24-hour period. Specific "gold-standard" measures exist that are typically used in lab-based settings. For sleep, polysomnography is the "gold-standard" measure. It is typically used to screen for sleep irregularities based on detailed measures of sleep duration, quality, and architecture. However, polysomnography is a costly process that usually requires the participant to sleep in a designated sleep laboratory attached to numerous wires and sensors, which can disrupt the very sleep it is trying to record (Scholle et al., 2003). Therefore, the balance between validity and cost generally does not warrant the use of polysomnography for determining sleep duration in field settings. In room calorimetry is a "gold standard" method of directly or indirectly determining the energy expenditure of a participant, which can be classified into the metabolic equivalents of sedentary behaviour, light physical activity, or moderate to vigorous physical activity. Similar to polysomnography, in room calorimetry is costly and does not adequately measure free-living conditions (Seale & Rumpler, 1997). Based on the limitations of these proposed gold-standards, these methods are most useful as criterion measures to determine the validity of tools and techniques that can then be used in field settings and population-based samples.

Using one technique or tool capable of accurately measuring the movement behaviour spectrum in free-living conditions would reduce participant burden (e.g., not wearing multiple devices) and researcher costs (e.g., not purchasing multiple devices). Specifically, direct observation, proxy-report (e.g., questionnaire, log sheets, time use diaries), and accelerometers can measure sleep, sedentary behaviours/stationary behaviour, and physical activity in early years children (Sadeh, 2015; Trost, 2007). Direct observations can be considered a valid and feasible gold-standard alternative for field-based studies when measuring movement behaviours in free-living conditions, and have been used to assess total sleep, sedentary behaviour, and physical activity (Meltzer, Montgomery-Downs, Insana, & Walsh, 2012; Welk, 2002). While it is considered a valid and reliable tool to assess movement behaviours (Klesges et al., 1984; Puhl, Greaves, Hoyt, & Baranowski, 1990; Thoman, 1990), directly observing an individual for 24-hours would be highly labour-intensive and thus not a feasible approach to determine habitual levels of movement behaviours. One approach that can increase feasibility is measuring children's movement behaviours via proxy-report (e.g., questionnaires, time use diaries). However, the feasibility gained from measuring all movement behaviours via proxy-report is at the expense of validity and reliability (Goodlin-Jones, Sitnick, Tang, Liu, & Anders, 2008; Hidding, Altenburg, Mokkink, Terwee, & Chinapaw, 2017; Sadeh, 2004, 2015; Sirard & Pate, 2001). Accelerometers can arguably offer the best field-based solution to overcome the limitations of low feasibility (i.e., direct observation) and low validity/reliability (i.e., proxy-report) of other movement behaviour measurement tools (Esliger, Copeland, Barnes, & Tremblay, 2005). Thus, accelerometers have been suggested as a feasible, reliable, and valid tool for measuring isolated movement behaviours in samples of early years children (Janssen et al., 2013; Sadeh, Acebo, Seifer, Aytur, & Carskadon, 1995), though efforts are needed to measure all movement behaviours with one device. Further, a vast amount of accelerometer methodological decisions, including data collection and data processing decisions, can influence validity, reliability, and feasibility (Cliff, Reilly, & Okely, 2009; Migueles et al., 2017).

2.2.1.1 Accelerometer Data Collection Decisions

The main data collection decisions, specific to accelerometery research, include: model and brand selection, wear-site, wear time protocol, sampling frequency, filters, epochs, data cleaning protocols (definitions of reliable data and participants), and movement behaviour classification.

2.2.1.1.1 Brand and Model Selection

Perhaps the most immediate decision is the model of accelerometer to use. The Actigraph, Actical, GENEActiv, SenseWear, and Axivity are the most common accelerometer brands able to measure sleep, sedentary behaviour, and physical activity (Doherty et al., 2017; Quante et al., 2015; Rosenberger, Buman, Haskell, McConnell, & Carstensen, 2016). However, the majority of accelerometer studies measuring early years children's movement behaviours have been conducted with the ActiGraph (Cliff et al., 2009; Migueles et al., 2017). To improve comparability with other preschool-aged children's research using accelerometers, the ActiGraph WGT3X-BT accelerometer will be used in the manuscripts outlined in this dissertation. To discuss the most relevant literature, further sections of this literature review will be specific to the ActiGraph accelerometer and preschool-aged children. However, when information cannot be found relevant to this accelerometer brand and age group, information on other brands and age groups will be used to bridge the gaps and/or highlight future research needs.

2.2.1.1.2 Wear-site

Accelerometer wear-site is another a priori decision that predominantly consists of either the wrist or right hip locations. This is an interesting component of movement behaviour research as physical activity and stationary time measurement have traditionally used the right hip wear-site; whereas sleep measurement has traditionally used the wrist wear-site. Therefore, to consolidate these two evolving areas of research, evidence would be needed for adequate sleep measurement at the waist wear-site, or adequate stationary time and physical activity measurement at the wrist wear-site. Johansson, Larisch, Marcus, and Hagstromer (2016) compared the non-dominant wrist to the left hip wear sites and found that both sites had excellent concurrent validity when sedentary time and MVPA were compared to direct observation. However, no explanation was given as to why the wrist site was not compared to the more frequently used right hip wear site. Considering hip wear site cut-points used in this study were originally created specifically for the right hip, this study may be limited in its ability to compare previous/current best-practice cut-points to the authors newly created wrist cut-points. Additionally, Smith, Galland, Taylor, and Meredith-Jones (2020) compared the ActiGraph GT3X+ for sleep classification at the non-dominant wrist and right hip in children 5-8 years of age. Compared to overnight polysomnography estimates of total sleep, significant mean differences were found for the hip wear site (21 minutes) and the wrist wear site (-26 minutes). However, the authors recommended the hip wear site for measuring overnight sleep duration based on the waist wear sites improved accuracy in total sleep and duration of time between sleep onset and offset (Smith et al., 2020). Thus, future work could use the right hip wear site for measuring movement behaviours in preschool-aged children with the ActiGraph accelerometer, though some work would be required to determine the capability of detecting daytime sleep (see Section 2.2.1.2.4.3).

2.2.1.1.3 Wear Time Protocol

Protocols for accelerometer wear time in preschool-aged children generally consist of wearing during childcare, waking or sleeping time, or full 24-hours. To measure all movement behaviours with one device would mean it is preferential to use the 24-hour wear-time protocol. No studies were found comparing different wear-time protocols in early years children. However, in a sample of older children, Tudor-Locke et al. (2015) found that a 24-hour wear time protocol improved compliance compared to a waking hours protocol. If this is also true in preschool-aged children, it would further support the use of measuring all movement behaviours with one device. Therefore, research comparing protocols are needed in this age group to determine if similar benefits exist.

2.2.1.1.4 Sampling Frequency

The frequency of data collection determines the rate at which the raw ActiGraph accelerometer data is collected. The most common frequency is 30 Hz, which also coincides with the default setting when programming ActiGraph accelerometers. Of the preschool-aged studies found in this literature review, only one study used a non-default sampling frequency, as Costa et al. (2014) used an 80Hz sampling frequency. No research has been conducted specific to the early years to determine the ideal sampling frequency. However, in a sample of university students Brønd and Arvidsson (2016) found that compared to the 30 Hz frequency, the 40 Hz and 100 Hz frequencies had higher counts/minute with differences becoming more dramatic at higher intensities of activity. Brønd and Arvidsson (2016) thus recommended to use the default 30 Hz sampling frequency to maximize comparability with previous studies, and allow the use of previously calibrated cut-points.

2.2.1.2 Accelerometer Data Processing Decisions

After data is collected, accelerometer data must be processed to produce meaningful results. This means taking raw accelerometer data and deciding on: filters, epochs, data cleaning protocols (definitions of reliable data and participants), and movement behaviour classification. ActiGraph accelerometer data can be downloaded in the raw format and researchers can decide on filters and what epoch to aggregate data, or filters and epochs can be chosen from the ActiLife software to generate counts.

2.2.1.2.1 Filters

ActiGraph data are filtered to remove movement occurring at too low or high of a frequency (or intensity), based on what is deemed as biologically plausible. When data is being processed in ActiLife the two filter options are the normal filter or the low-frequency extension filter. The normal filter detects accelerations in the 0.25-2.5 Hz range, which can result in some vigorous intensity physical activity being classified as moderate physical activity (Brønd & Arvidsson, 2016; John, Miller, Kozey-Keadle, Caldwell, & Freedson, 2012). While it is known that the low-frequency extension filter detects accelerations below the 0.25 Hz frequency, it is not known how much lower the frequency is set. In a sample of school-aged children, the low frequency extension filter was shown to be more sensitive compared to the normal frequency filter for classifying sleep (Hjorth et al., 2012). Thus, recommendations have been made to use the low-frequency extension filter when examining sleep, while the normal filter should be used for other movement behaviours (Hjorth et al., 2012).

2.2.1.2.2 Epochs

Epoch refers to the length of time over which accelerometer data are averaged. Previously epoch length was an a priori decision, but advances in memory capacity of accelerometers have enabled this choice to become a post-hoc decision as data is now collected in its raw form. Advances in the memory of accelerometers is also responsible for trends in the epochs used when studying preschool-aged children. Initially 1-minute epochs were used until memory capacity reached a level that supported shorter epochs (e.g., 15 seconds) over several days. Using epochs shorter than 1-minute is considered advantageous since children typically have sporadic and intermittent movement patterns. For instance, the use of shorter epochs results in higher prevalence of MVPA (Colley, Harvey, Grattan, & Adamo, 2014; Vale, Santos, Silva, Soares-Miranda, & Mota, 2009) and sedentary time, as well as lower levels of LPA in early years children (Colley et al., 2014), which could indicate the shorter epoch more accurately captures the sporadic movement profile (e.g., short bouts of stationary time and MVPA) in this age group. The majority of calibration studies in this age range use 15 second epochs (Evenson, Catellier, Gill, Ondrak, & McMurray, 2008; Pate, Almeida, McIver, Pfeiffer, & Dowda, 2006; Pulakka et al., 2013; Sirard, Trost, Pfeiffer, Dowda, & Pate, 2005; Trost, Fees, Haar, Murray, & Crowe, 2012; Van Cauwenberghe, Labarque, Trost, Bourdeaudhuij, & Cardon, 2011b) but some recent studies have used 5 second epochs (Costa et al., 2014; Johansson, Ekelund, Nero, Marcus, & Hagströmer, 2015; Johansson et al., 2016). However, validation studies comparing newly calibrated 5-second epochs included methodological choices that limit comparability with previously established cut-points (i.e., different frequency and wear-site) (Costa et al., 2014; Johansson et al., 2016). Future calibration and validation studies should explore epoch choice while remaining consistent in other domains, thus allowing comparability. Future research not seeking to calibrate or validate, could use 15 second epochs based on the breadth of validation and calibration studies in this domain.

2.2.1.2.3 Data Cleaning Protocols

Steps involved in data cleaning include defining a non-wear time definition, a valid day, and the number of valid days. Non-wear time is the data that is recorded on the accelerometer when a participant is not wearing the accelerometer (e.g., while swimming). No studies could be found comparing non-wear time definitions in early years children. Definitions in older ages range from a minimum of 10-180 minutes (Cliff et al., 2009). Further, 20 minutes motionless (or zero counts) has been proposed as a suitable non-wear time definition for preschool-aged children (Cliff et al., 2009). However, when using 24-hour wear protocols, it is recommended to categorize sleep before non-wear time, as some sleep could be misclassified as non-wear time (Tudor-Locke et al., 2015).

While no minimum hours per night are suggested for sleep measurements, three (age 60 months) to five days (age 48 months) of accelerometer measurement have been proposed for reliable estimates of sleep duration (Acebo et al., 1999). Six to eight hours of wear time have been reported as representing a valid day of stationary time and physical activity via accelerometery (Addy, Trilk, Dowda, Byun, & Pate, 2014; Bingham et al., 2016a; Hinkley et al., 2012; Hislop et al., 2014), and 3 to 9 days for reliable estimates of habitual physical activity and sedentary behaviour (Addy et al., 2014; Bingham et al., 2016a; Byun, Beets, & Pate, 2015; Hinkley et al., 2012; Hislop et al., 2014). Of interest, when hours/day of available data increases, the number of days needed for reliable estimates of habitual physical activity decreases (Hinkley et al., 2012). Considering the improved compliance of a 24-hour wear time protocol, the lower end of necessary days could be used to estimate habitual physical activity and stationary time.

2.2.1.2.4 Movement Behaviour Classification

Creating, or testing, a method that classifies movement behaviours requires a ground truth estimate of the behaviour of interest, or the observations that classification predictions would attempt to achieve perfect agreement with (Lemoigne, 2008). Ground truth classification should use a method that is considered a true gold-standard (e.g., polysomnography, in-room calorimetry), or valid and feasible alternatives in field-based studies (e.g., direct observation, visually inspected accelerometer data) (Kushida et al., 2005; Welk, 2002). While true gold-standards represent the closest approximation to the behaviour of interest, as previously mentioned (section 2.2.1) these methods are not always feasible in field settings and a practical gold-standard is often needed. After choosing a ground truth measure there are two methods for classifying individual movement behaviours—setting cut-points that represent each category and using algorithms to predict the category (Migueles et al., 2017). For instance, with cut-points a researcher could determine that when an accelerometer registered 420 or greater counts/15-secound epoch, children were generally engaged in MVPA according to direct observation. Whereas, with algorithms a researcher could determine the probability that nighttime sleep was occurring in a specific epoch, with a 20-minute range of vertical accelerations and approximated posture. In fact, like most statistical analyses, an algorithms task is to find a signal within the noise (or pattern within the observations) of data it is presented—in this case sleep classification is based on processing accelerometer signals. While both techniques can be used to classify all movement behaviours, currently the cut-point method is most often used for physical activity and stationary time whereas algorithms are used to classify sleep (Migueles et al., 2017).

2.2.1.2.4.1 Physical Activity

Several validation studies have been conducted to determine optimal physical activity cut-points in early years children. Vigorous physical activity can be misclassified as moderate physical activity in what is termed the plateau effect (John et al., 2012), so MVPA cutpoints are preferable to MPA and VPA alone. Of the validation studies found (Alhassan et al., 2017; Costa et al., 2014; Janssen et al., 2013; Johansson et al., 2016; Oftedal, Bell, Davies, Ware, & Boyd, 2014; Trost et al., 2012; Van Cauwenberghe, Gubbels, De Bourdeaudhuij, & Cardon, 2011a) the most extensive and up-to date study was performed by Janssen et al. (2013). Within this study 40 4-6 year-old children wore an ActiGraph GT3X on the right hip inside an in-room calorimeter while having activity intensity classified using direct observation (i.e., the Children's Activity

Rating Scale). The protocol consisted of performing a set 100-minute activity that included age appropriate activities (e.g., hopscotch, dancing, dressing up in costumes). Using the vertical axis, 15-second epochs were collected, and MVPA was classified according to the Pate (≥420 counts/15 seconds), Evenson (≥574 counts/15 seconds), Van Cauwenberghe (≥585 counts/15 seconds), Puyau (≥799 counts/15 seconds), and Sirard (≥813/891 counts/15 seconds) ActiGraph cut-points. From this validation study, ROC curves were conducted and the best cut-point for MVPA was the Pate cut-point (AUC = 0.72, Sensitivity=54.2%, Specificity=88.9%). Therefore, the Pate ActiGraph, right hip, MVPA cut-point (≥420 counts/15 seconds) could be considered the best choice of cut-point for preschool-aged children. Additionally, the best cut-point for LPA was the Evenson cut-point (AUC=0.65, Sensitivity=54.8%, Specificity=74.8%); however, this cut-point must be considered in conjunction with stationary time cutpoints.

2.2.1.2.4.2 Stationary time

All validation studies examining the optimal cutpoints for stationary time in early years children have previously been listed above for physical activity (Alhassan et al., 2017; Costa et al., 2014; Janssen et al., 2013; Johansson et al., 2016; Oftedal et al., 2014; Trost et al., 2012; Van Cauwenberghe et al., 2011a). Similarly, the most extensive and up to date validation study for preschool-aged children was performed by Janssen et al. (2013). Children followed a set of age-specific sedentary behaviours (e.g., reading with a cassette, colouring, watching TV) for 47 minutes while wearing the ActiGraph inside the in-room calorimeter and being directly observed. Using the vertical axis, 15-second epochs were collected, and stationary time was classified according to the Evenson (≤25 counts/15 seconds), Pate (≤37 counts/15 seconds), Puyau (≤199 counts/15 seconds), Reilly (≤199 counts/15 seconds), Van Cauwenberghe (≤372 counts/15 seconds), and Sirard (≤363/398 counts/15 seconds) ActiGraph cut-points. Janssen et al. (2013) determined with ROC curves that the best cut-point for stationary time was the Evenson cut-point (AUC=0.80, Sensitivity=86.7%, Specificity=72.9%). Therefore, the Evenson (≤25 counts/15 seconds) ActiGraph, right hip, stationary cut-point (≤25 counts/15 seconds) could be considered the best choice of cut-point for preschool-aged children.

2.2.1.2.4.3 Sleep

No sleep classification techniques have been developed specifically for preschool-aged children using the ActiGraph accelerometer (Migueles et al., 2017). However, the Cole-Kripke and Sadeh algorithms are two common approaches that have been used to classify ActiGraph data as sleep in older populations (Cole, Kripke, Gruen, Mullaney, & Gillin, 1992; Sadeh et al., 1995; Sadeh, Alster, Urbach, & Lavie, 1989). Further, techniques building on the Cole-Kripke and Sadeh algorithms have been applied to ActiGraph data to classify sleep in older children. Lastly, machine learning approaches have been used to classify sleep with high levels of accuracy.

The Cole-Kripke algorithm was calibrated with polysomnography as the criterion measure in 20 older adults with and without sleep and psychiatric disorders using the Motionlogger Actigraph (Ambulatory Monitoring, Inc., Ardsley, NY), and validated in 21 older adults with and without sleep and psychiatric disorders. Linear regression models were created to predict sleep based on the current epoch, the previous 4 minutes, and the following 2 minutes (see equation 1 below). Weighting was assigned to each epoch based on an optimization protocol (adjusting the value of each constant until the smallest sum square difference is reached between the predicted sleep and the criterion sleep). Specific to Actigraph's Actilife software, all values are derived from the vertical axis and must be in 1-minute epochs, values are scaled by 100, any value over 300 is truncated to 300, and probability of sleep (PS) calculations less than 1 are considered as sleep ($PS < 1$ = sleep; $PS \geq 1$ = awake).

Equation 1:

$$PS = .001 * [(106 * Epoch_{x-4}) + (54 * Epoch_{x-3}) + (58 * Epoch_{x-2}) + (76 * Epoch_{x-1}) + (230 * Epoch_{x}) + (74 * Epoch_{x+1}) + (67 * Epoch_{x+2})]$$

No studies have used this algorithm in preschool-aged children with the ActiGraph. However, Hjorth et al. (Hjorth et al., 2012) found the algorithm categorized sleep in hip worn ActiGraph GT3X+'s with good sensitivity but low specificity in a sample of school-aged children. The sensitivity and specificity values were calculated by comparing the waist worn site to the wrist worn site, so these values are more reflective of the appropriateness of wear-sites and not the algorithm compared to a criterion. However, the Cole-Kripke algorithm was compared to the Sadeh algorithm with the Cole-Kripke algorithm having higher sensitivity and the Sadeh algorithm having higher specificity. Of note, while significant differences between the two algorithms existed, the differences in sensitivity were 0.65% while the differences in specificity were 11.6%. Thus, the Sadeh algorithm may be advantageous over the Cole-Kripke algorithm in older children.

The count scale algorithm is similar to the Cole-Kripke algorithm in that it determines the probability of sleep (Wake = PS $\geq$ 1; Sleep = PS < 1) based on an optimized formula with different weights assigned to the current epoch, previous 4 epochs, and next 2 epochs (See equation 2 below). The main difference from the Cole-Kripke algorithm, aside from the different weights for the epochs, is that prior to running the algorithm the average of all non-zero epochs is calculated and every epoch is then divided by this number. The count-scale algorithm was developed by Galland et al. (2012) to detect daytime sleep in early years children (Galland, Kennedy, Mitchell, & Taylor, 2012) but is also capable of determining night sleep (Galland et al., 2016). The detection of daytime sleep using accelerometers has been identified as a major gap in the literature (Galland, Meredith-Jones, Terrill, & Taylor, 2014a). This gap can partly be explained by the difficulties in distinguishing naps from non-wear time or stationary behaviours. For instance, if a child naps during the day the accelerometer would measure little or no activity. This would be similar to the accelerations detected while the accelerometer is off or while in a car seat during a long car-ride, thus nap time could be misclassified as non-wear time or stationary time. Within this study infants (10-22 weeks) were measured during a nap in a sleep laboratory that was disturbed with an auditory stimulation (Galland et al., 2012). Actical accelerometers were worn on the shin, and polysomnography was also used to score sleep as quiet sleep, active sleep, and indeterminate sleep. Using this data, the count scale algorithm was created, which was able to detect sleep-wake states with higher level of agreements with polysomnography compared to the Sadeh and Cole-Kripke algorithms.

Equation 2:

$$PS = 2.7 * [(1 * Epoch_{x-4}) + (2 * Epoch_{x-3)} + (3 * Epoch_{x-2}) + (4 * Epoch_{x-1}) + (5 * Epoch_{x}) + (3 * Epoch_{x+1}) + (1 * Epoch_{x+2})]$$

Since the count scale algorithm is scaled relative to the data, authors claim it is generalizable across accelerometer models and site placements. This generalizability was seen when older children (1-5 years) were monitored with waist-worn Acticals and agreement with sleep diaries was “moderate” to “almost perfect” (Galland et al., 2016). Meredith-Jones and colleagues (2016) compared the count-scaled algorithm, the Sadeh algorithm, and parental diary as a means of removing night sleep, to derive estimates of daily stationary time and physical activity using ActiGraph GT3X accelerometers in children 4-9 years old. Estimates of MVPA did not differ between all approaches, but they did all produce different estimates of stationary time and total wear time. Additionally, for counts per minute and light physical activity the parental diary and Sadeh algorithm were statistically equivalent, while the count scaled algorithm differed from both; however, authors concluded these differences were relatively small. Sleep estimates were not presented in this article, likely due to the lack of a ground truth sleep estimate. Thus, conclusions could not be made regarding the count-scaled algorithms usefulness for classifying sleep using the ActiGraph. However, a follow-up study compared the count-scaled algorithm to polysomnography to classify overnight sleep in children 5-8 years old with ActiGraph GT3X+ and Actical accelerometers (Smith et al., 2020). Smith et al. (2020) found that waist worn ActiGraph predictions of sleep reached an overall accuracy of 88.2% (95% Confidence Intervals: 84.1, 91.3), but found a significant mean difference of 21 minutes between the count-scale algorithm and polysomnography. No studies classifying daytime sleep with the count-scale algorithm in ActiGraph accelerometers were found.

The Sadeh algorithm was calibrated with polysomnography as the criterion measure in 10 adults with wrist-worn AMA-32 accelerometer (Ambulatory Monitoring, Inc., Ardsley, NY), and validated on a sample of 10 adults and 16 adolescents. The algorithm was created from the calibration sample by performing a stepwise discriminant analysis to identify which variables best predicted sleep-wake cycles. Subsequently an equation was created using four variables representing A) the average number of activity counts during the scored 1-minute epoch and the 5-minute window before and after the scored epoch (total window = 11 minutes), B) the number of epochs in the 11-minute window between 50-99 counts/minute, C) the standard deviation of the scored epoch and the 5-minute window before the scored epoch (total window = 6 minutes), and D) the natural logarithm of the scored epoch + 1. Using these four variables (See equation 3 below) PS is calculated with positive values classified as sleep and negative values classified as wake. Specific to ActiGraph's Actilife software, all values are derived from the vertical axis and must be in 1-minute epochs, any epoch greater than 300 counts/minute is truncated to 300, and any PS values greater than -4 are classified as sleep (PS ≥ 4 = sleep; PS < -4 = awake) (ActiGraph Support Center, 2017b).

Equation 3:

$$PS = 7.6010 - 0.0605A - 1.0800B - 0.0560C - 0.7030D$$

Further research has examined the Sadeh algorithm for measuring total sleep time in children aged 4-11 years wearing an ActiGraph on the hip (Barreira et al., 2015; Hjorth et al., 2012; Kinder et al., 2012; Meredith-Jones et al., 2016; Tudor-Locke, Barreira, Schuna, Mire, & Katzmarzyk, 2014). One difference in study protocols is that some used parental logs to flag bedtime and wake time (Hjorth et al., 2012; Kinder et al., 2012), while others relied on algorithms to automate this process (Barreira et al., 2015; Meredith-Jones et al., 2016; Tudor-Locke et al., 2014). Tudor-Locke et al. (2014) modified the Sadeh algorithm to improve classification accuracy and fully automate the algorithm. Specifically, data was classified as Sleep or Wake using the Sadeh algorithm, then any wake minute was reclassified as sleep when the ActiGraph inclinometer data was in the off position, and finally smoothing rules were created. The smoothing rules consisted of flagging the sleep onset period as the first five consecutive minutes classified as sleep, flagging the wake onset period as the first 10 consecutive minutes classified as wake, and only considering this a sleep period if 160 minutes elapsed between the two flags. Authors found a non-significant mean difference of 2 minutes when their modified algorithm was compared to visual inspection for nighttime sleep. Building on this refinement, Barreira et al. (2015) adjusted their modified algorithm by 1) only allowing sleep onset between 19:00 and 5:59, 2) changing the wake onset definition to 10 consecutive minutes between 5:00 and 11:58 or 20 consecutive minutes between 21:40 and 4:59, and 3) reducing the sleep period definition from 160 minutes to 20 minutes. Using this modified algorithm, a non-significant mean difference of 9 minutes for nighttime sleep was found when compared to a log sheet combined with the Sadeh algorithm (Barreira et al., 2015). However, none of these studies were in preschool-aged children, and thus did not examine daytime sleep. Further, modifications made by Barreira would prohibit classification of daytime sleep (Barreira et al., 2015). Thus, future research could test the Sadeh and modified Sadeh algorithm for sleep classification in data containing naps, to determine the best methods for preschool aged children.

Recently, I explored several algorithms (i.e., Sadeh, Tudor-Locke, Cole-Kripke, and count scale) to classify sleep in preschool-aged children with waist-worn ActiGraph WGT3X-BT accelerometers using a ground truth estimate from a combination of visual inspection, guided by previously published heuristics (Tudor-Locke et al., 2014), and sleep diaries. This data was presented at the 2019 International Conference on Ambulatory Monitoring of Physical Activity and Movement. It is important to note for submission the count scale algorithm was omitted due to very low accuracy. However, I determined none of these algorithms could accurately classify daytime and nighttime sleep. Though these preliminary findings should be interpreted with caution as they have not been published in a peer-reviewed journal, it was concluded that further efforts should be made to develop algorithms specific to this age-range using the ActiGraph WGT3X-BT.

Recently, Willetts et al (2018) extracted features from raw data and applied machine learning techniques to successfully classify sleep (97% Accuracy) in adults using the Axivity AX3 accelerometer. Specifically, 30 second non-overlapping windows were used to generate a vector of 126 features (i.e., time domain, frequency domain, angular, correlation, and demographic features). Random forest models were then trained on ground truth data for six behaviour labels (wearable camera: “bicycling”, “mixed”, “sit/stand”, “vehicle”, “walking”; sleep diary [or full time-use diary if missing]: “sleep”). To account for the unbalanced proportions within the six behaviour labels (e.g., much more sleep than bicycling) random forest models used a balanced approach by down-sampling to the rarest category. For instance, if the rarest category has 800 observations, then each category randomly samples 800 observations with replacement for a total of 4800 observations (800 observations * 6 categories). Random forest models were trained and tested using leave one subject out cross validation, such that each model would sequentially remove one participant’s data during training then test the results on that omitted participant. To account for the temporal attributes of accelerometer data (e.g., nighttime sleep generally occurs in a long continuous bout, while MVPA is accumulated throughout the waking day), hidden Markov modeling was performed after random forest modeling. Hidden Markov modeling improved the accuracy of sleep prediction from 90% to 97%. Considering the lack of ActiGraph sleep classification techniques specific to preschool-aged children with proven validity or reliability, future studies could apply similar machine learning techniques to this age group.

2.2.1.3 Accelerometer additional features

Within the Actigraph WGT3X-BT there are several additional features that are either data collection or data processing steps, which can be used to gather data beyond movement. Specifically, the proximity detection, ambient light sensor, and posture estimation features could be useful to researchers.

Proximity detection is the only data collection decision of these features. The reason this must be set before data collection is because the feature decreases the battery life. With the proximity detection feature, accelerometers can be programmed to either emit or detect a

Bluetooth signal (ActiGraph Support Center, 2014). Detection of this emitted signal can then be used as an estimate of proximity between the two accelerometers. While determining the actual distances between the devices is hypothetically possible in lab-scenarios, it is less feasible in field settings. However, Kuzik and Carson (2018) have tested the validity of this feature as an estimate of presence or absence of close-proximity between a parent and early years child. Accelerometer-derived parent-child proximity demonstrated good concurrent validity (receiver operating characteristic (ROC) area under the curve (AUC): 0.84; 95% confidence intervals: 0.84, 0.85) when compared to parental time-use diaries.

Ambient light sensors are mounted in the WGT3X-BT model accelerometers, and are constantly collecting data—making this a data processing decision (ActiGraph Support Center, 2016). By measuring the differences in the intensity of light some researchers have been able to accurately distinguish whether children are indoors or outdoors via Actigraph accelerometers (Flynn et al., 2014; Tandon, Saelens, Zhou, Kerr, & Christakis, 2013). Future research could also use this feature to help distinguish when a child is sleeping, since this should hypothetically be a time of no/low light exposure.

Lastly, the Actigraph WGT3X-BT has a data processing inclinometer feature that is able to estimate posture (ActiGraph Support Center, 2017a). Since ActiGraph's measure movement with a capacitive accelerometer, the force of gravity is constantly being measured. For example, if a person is wearing a hip-mounted accelerometer and standing perfectly vertical, the force of gravity would only be measured in the vertical axis. Similarly, if the accelerometer was removed and put down facing up, the force of gravity would only be measured in the sagittal axis. Specific postures are therefore estimated based on the force of gravity detected in the vertical (standing <17° or any movement >90 counts/15-seconds; sitting 17°-65°; and lying >65°) or sagittal axes (off <22°) (ActiGraph Support Center, 2017a). Given ideal conditions, this feature would be able to accurately determine posture, but the variability of the direction of static accelerations creates less than ideal conditions in field settings. For instance, estimates have shown that waist worn ActiGraphs do not perform well (classification accuracy: 72% lying, 58% sitting, and 74% standing) compared to thigh worn accelerometers (i.e., activPAL3, GENEActiv, and Actigraph classification accuracy: ≥93% lying, ≥91% sitting, and ≥93% standing) (Edwardson et al., 2016). However, as mentioned in section 2.2.1.2.4.3, the posture detection feature has helped researchers classify accelerometer derived sleep measured in older children (Barreira et al., 2015; Tudor-Locke et al., 2014).

2.2.2 Data analysis

Data with constant sum (values that always add to make a whole) and non-negative (values range from 0 to ∞) constraints pose a problem, since they are perfectly collinear as one part of the composition can perfectly predict the remaining parts. Further, traditional analytical techniques were created for data that could be mapped in real Euclidean space (any values ranging between -∞ and ∞), not in these constrained spaces. Karl Pearson in 1897 recognized that a constant sum constraint can lead to calculations of spurious correlations, since the numerators and denominators of the components contain common parts (Pearson, 1897). Further, logarithm transformations have allowed researchers to overcome the non-negative constraints (McAlister, 1879). Thus, Aitchison (1982) began treating non-negative and constant sum constrained data as a composition or proportion while performing a log ratio transformation to allow for analyses of this perfectly collinear data. This was the beginning of the field of compositional data analysis and led to the application of isometric log-ratio (ilr) transformations, otherwise known as orthonormal transformations, which can be expressed in real Euclidean space. Thus, representing compositional data as ilr coordinates allows for the application of common statistical techniques built for real Euclidean space data (e.g., regression analyses, MANOVA, discriminant analysis, clustering compositional analysis).

Contemporary compositional data literature has moved away from the need for a constant sum constraint. Pawlowsky-Glahn et al. (2015) state "*compositional data are vectors with strictly positive components that carry relative information*". Movement behaviour data consists of relative information. For instance, sleep would not be stated in absolute terms as 77 hours, since this would be meaningless without a denominator such as 77 hours/7 days, or 11 hours/day, or 0.46 of the composition of movement behaviours. Additionally, for the case of accelerometer derived movement behaviours, the denominator for 7 days would equal the total of all movement behaviours (and non-wear time) over seven days. Since these movement behaviours compete for time within the 7 days, there is a push and pull between movement behaviours when any change occurs. Consequently, any one movement behaviour duration is only meaningfully interpreted relative to the duration of all movement behaviours. Further, movement behaviour data consists of strictly positive values since it would be impossible to accrue a negative amount of any movement behaviour. Thus, movement behaviour data could be appropriately analyzed using compositional data analysis.

Traditionally the relationship between movement behaviours and health indicators was examined through linear regression analyses independently, and more recently mutual adjustments of one movement behaviour for another has been used to determine the independent effects of each movement behaviour on the health indicator of interest (Pedišić, 2014). Exploring this idea, Dumuid et al. (2017) used traditional multiple linear regressions to determine the effect of excluding one component of a composition at a time. More specifically, sleep, stationary time, LPA, and MVPA were used to predict BMI z-scores in four models (i.e., sleep excluded, stationary time excluded, LPA excluded, and MVPA excluded). Inconsistent results were seen in all four models, with some inconsistencies being minor (e.g., MVPA β: -0.011 to -0.016) and major (e.g., stationary time and sleep being both positively and negatively associated with BMI z-scores). Additionally, multicollinearity was tested in all four models and only one model (MVPA removed) suggested potential multicollinearity indicating that traditional methods to analyze compositional data can avoid detection of multicollinearity but can still produce spurious results. Therefore, compositional data analyses is recommended for all studies examining movement behaviour compositions (Pedišić et al., 2017).

2.2.2.1 Compositional data analysis examples

2.2.2.1.1 Descriptive data analysis

Two criteria for suitable descriptive analysis within compositional analysis are the ability to retain meaning when undergoing translation and rescaling (Aitchison, 1986). While mean/median and standard deviation/standard error are good representations of central tendency and dispersion for standard descriptive statistics, these calculations would lose meaning through translation and rescaling (Van den Boogaart & Tolosana-Delgado, 2013). Thus, compositional data analyses have unique representations of central tendency and dispersion. Central tendency or centre is defined by a vector of closed geometric means for all movement behaviours (see equation 4). Dispersion is then calculated with a variation matrix (see equation 5) that demonstrates the proportionality between two movement behaviours, and sample total variance (see equation 6) that demonstrates the compositions global dispersion.

Equation 4:

$$Centre\ (g) = C[g_1, g_2, \dots g_D], where\ g_j = \left(\prod_{i=1}^{n} x_{ij}\right)^{1/n}, j = 1,2, \dots D$$

Where x represents the j^{th} sub-component and D is the total number of sub-components (e.g., if x_1 = sleep, x_2 = stationary time, x_3 = LPA, and x_4 = MVPA; then D = 4), for a sample size of n.

Equation 5:

$$Variation\ Matrix = \begin{bmatrix} t_{11} & t_{21} & \cdots & t_{1D} \\ t_{21} & t_{22} & \cdots & t_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ t_{D1} & t_{D2} & \cdots & t_{DD} \end{bmatrix},\ t_{ij} = var\left(\ln \frac{x_i}{x_j}\right)$$

Where values range between 0 and 1, and the lower values indicate higher levels of proportionality (Van den Boogaart & Tolosana-Delgado, 2013).

Equation 6:

$$Total\ Variance = \frac{1}{2D} \sum_{i,j=1}^{D} t_{ij}$$

2.2.2.1.2 Compositional regression analyses

Regression analyses using compositional data can be done with compositional outcome or compositional exposure variables (Pawlowsky-Glahn et al., 2015). Further, models can be created that simultaneously consider the outcome and exposure variables as compositions (Filzmoser, Hron, & Templ, 2018). The ilr coordinates (see equation 7) are suggested for regression analyses to allows researchers to apply traditional analytical techniques developed for absolute data (e.g., regression analysis) to compositional data (Filzmoser et al., 2018; Pedišić et al., 2017).

Equation 7:

$$z_j = \sqrt{\frac{D-j}{D-j+1}}\, ln \frac{x_j}{\sqrt[D-j]{\prod_{k=j+1}^{D} x_k}} \text{ for j=1, 2,…, D-1}$$

Where z is a row vector with isometric log-ratio coordinates.

For instance if sleep, stationary time, LPA, and MVPA are measured then ilr transformations would progress as:

Equation 8:

$$x_1 = sleep, x_2 = stationary\ time, x_3 = LPA, and\ x_4 = MVPA$$

$$z_1 = \sqrt{\frac{3}{4}}\, ln \frac{x_1}{\sqrt[3]{x_2 x_3 x_4}}$$

$$z_2 = \sqrt{\frac{2}{3}}\, ln \frac{x_2}{\sqrt[2]{x_3 x_4}}$$

$$z_3 = \sqrt{\frac{1}{2}}\, ln \frac{x_3}{\sqrt[1]{x_4}}$$

Regression models can then be created with these ilr transformed variables as usual. Building on the following example, the composition of movement behaviours can be considered the exposure variables in regression analyses:

Equation 9:

$$y = \beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3 + \varepsilon_i$$

The order which sub-components are transformed does not alter interpretation of the significance, fit, or intercept of the full models; however, individual β values are interpreted differently (Pawlowsky-Glahn et al., 2015). Specifically, the only meaningful β is β_1, which represents the significance and direction of the relationship between z_1, relative to z_2 and z_3, and y. Therefore, to determine the associations for each behaviour (relative to the other behaviours) a total of D regression models must be created, and for each model ilr transformations are calculated after rotating subcomponents such that x_1 becomes x_D and $x_{j>1}$ becomes x_{j-1}. A technique known as creating pivot coordinates. Once pivot coordinates are created, they can be used to build several regression models to understand the contribution of each part of the composition as an exposure and/or outcome variable. While pivot coordinates can be used to determine the significance and direction of relationships in regression analyses, log-ratio transformations prohibit an understanding of the magnitude of relationships, since the unit is not retained.

To improve the interpretability of compositional regression analyses Dumuid et al. (2019) put forward the compositional isotemporal substitution model. The premise for this model is to predict the value of an outcome variable using two compositions, then subtract these two predictions to calculate the hypothetical difference in the outcome variable. The first composition is the base composition of movement behaviours, while the second composition is the base composition with hypothetical substitutions or reallocations of time. Using the first composition a regression model is created, and the mean value of the outcome variable can be predicted using the beta coefficients, and the geometric means of the ilr coordinates. For instance, the previous example from equation 9 could be used to calculate the mean value of y:

Equation 10:

$$y_{mean} = \beta_0 + \beta_1 z_{1Geo\,mean} + \beta_2 z_{2Geo\,mean} + \beta_3 z_{3Geo\,mean} + \varepsilon_i$$

Then time can be reallocated by adding and subtracting an equivalent amount of time from parts of the composition. This can either be done as a one-for-all substitution (e.g., add 30 minutes of MVPA, subtract 30 minutes from the remainder of the composition) or as a one-for-one substitution (e.g., add 30 minutes of MVPA, subtract 30 minutes of LPA). This new reallocated time composition can then be used to calculate ilr coordinates, and the mean of these coordinates can be used to calculate the mean of y after substitutions (Sub):

Equation 11:

$$y_{Sub\,mean} = \beta_0 + \beta_1 z_{1Sub\,Geo\,mean} + \beta_2 z_{2Sub\,Geo\,mean} + \beta_3 z_{3Sub\,Geo\,mean} + \varepsilon_i$$

Finally, the change in y can be calculated to estimate the effects of the time reallocation:

Equation 12:

$$\Delta y = y_{mean} - y_{Sub\,mean}$$

2.3 Outcomes of health-related time-use compositions

2.3.1 Domains of health for early years children

According to the lifespan perspective three broad domains of development exist that can aide in grouping and identifying relevant health outcomes or indicators: physical, cognitive, and social-emotional development (Berk, 2013). Physical development includes physical changes to the body (e.g., size, shape, proportion, appearance), perceptual and motor abilities (e.g., hearing, grasping) and physical health and function (e.g., hypertension, puberty). Cognitive development includes intellectual abilities such as language, attention, imagination, problem solving, creativity, knowledge, and memory. Finally, social-emotional development includes capacity to understand, manage, and express emotions, as well as develop positive relationships with others (e.g., parents, peers) (Cohen, Onunaku, Clothier, & Poppe, 2005). Specific health indicators related to physical, cognitive, and social-emotional development that are critical or important for movement behaviours in early years children have been previously identified. More specifically, during the development of the *Canadian 24-Hour Movement Guidelines for the Early Years*, critical and important health indicators related to the exposures of sleep, sedentary behaviour, and physical activity were decided upon through expert consensus to include in three systematic reviews (Tremblay et al., 2017b). A fourth systematic review combined the indicators from the three individual reviews, thus highlighting critical and important health indicators related to all movement behaviours (Kuzik et al., 2017). The majority of health indicators were related to physical development including: adiposity (e.g., body fat estimates, waist circumference, body mass index), motor development (e.g., gross and fine motor skills), fitness (e.g., endurance, strength), growth (e.g., height, head circumference, weight), bone and skeletal health (e.g., bone density, bone mineral content), cardiometabolic health (e.g., insulin resistance, blood pressure, blood lipids), and risks (e.g., injury/harm). However, cognitive development (e.g., executive functions, language development) and psychosocial health/emotional regulation (e.g., self-efficacy, pro-social behaviour, social functioning, temperament, hyperactivity/impulsivity) were also included, which capture the cognitive and social-emotional domains of development.

2.3.1.1 Physical development

From a lifespan development perspective, physical development includes bodily growth (e.g., height, weight), perceptual and motor abilities (e.g., hearing, grasping) and physical health and function (e.g., adiposity, hypertension, puberty) (Berk, 2013). Preschool-aged children typically undergo bodily changes (e.g., increased height, increased muscle mass, decreased adiposity) that facilitate increased motor abilities, allowing the child to use their new body to better navigate their surroundings (Berk, 2013). Further, aspects of physical development in preschool-aged children, such as height, adiposity, and motor abilities or skills have demonstrated relationships with disease risk and cognitive development later in life (Batty et al., 2009; Must & Strauss, 1999; Piek, Dawson, Smith, & Gasson, 2008).

2.3.1.1.1 Growth

Growth is typically conceptualized as the bodily changes in length and weight, and can be categorized in segments (e.g., trunk weight, standing height) and proportions (e.g., body mass index). Some measures of growth have an overlap with adiposity indicators (e.g., body mass index) and will be detailed in Section 2.3.1.1.2. However, adult height is inversely associated with cardiovascular disease and total mortality (Batty et al., 2009), and children's height is a predictor of adult height (Cole & Wright, 2011).

2.3.1.1.2 Adiposity

Adiposity accumulation is related to growth as a proportion, in that it is often considered in relation to other anthropometric measurements. Distinguishing between growth and adiposity is important though, as evidence suggests adiposity over-accumulation, or obesity, is associated with numerous physical, cognitive, and social-emotional diseases and health risks acutely in preschool-aged children and later in adulthood (Must & Strauss, 1999). Further, obesity begins in early childhood and tracks into adulthood, making preschool-aged children an important age range to study (Geserick et al., 2018).

2.3.1.1.3 Motor skills

Motor skills are the bodily movements which children use to navigate their environment and are classified as gross motor skills (larger muscle group movements for ambulation or object manipulation), and fine motor skills (smaller muscle group movements requiring precision) (Berk, 2013). Evidence exists relating measurements of gross motor skills in the preschool years to later cognitive development outcomes in school-aged children (Piek et al., 2008). Further, research suggests there is a low to moderate association between motor skills in early childhood and physical activity in school-aged children (Robinson et al., 2015).

2.3.1.2 Cognitive development

From a lifespan development perspective, cognitive development involves transformations in intellectual abilities including attention, memory, language, knowledge, and creativity (Berk, 2013). In preschool-aged children, rapid development in the frontal cortex occurs that supports the emerging executive functions and language development (Berk, 2013). Furthermore, executive functions and language development are strongly correlated (Gooch, Thompson, Nash, Snowling, & Hulme, 2016) and predictors or indicators of school readiness (High, 2008; Shaul & Schwartz, 2014).

2.3.1.2.1 Language

Language development during the preschool years involves the expansion of vocabulary and syntax of the native language (Berk, 2013). Language development follows a common trajectory but there is much individual variability for timing and rate of language development (Fenson et al., 1994). This variability is influential as a larger vocabulary in early life is predictive of later academic success and behavioural functioning (Morgan, Farkas, Hillemeier, Hammer, & Maczuga, 2015).

2.3.1.2.2 Executive functions

Many models of executive functions have been proposed (Wiebe & Karbach, 2018). Some consistent elements of these models include conceptualizing executive functions as an umbrella term for a set of skills commonly including working memory, inhibitory control, cognitive flexibility, reasoning, problem solving, and planning (Diamond, 2016). However, for early years children the three most emergent core executive functions are: working memory, inhibitory control, and cognitive flexibility (Diamond, 2013). Working memory is the ability to hold information in mind (e.g., visual and verbal information), and work with it (Cowan, 2008). Holding one or two pieces of information in mind emerges at age 9-12 months, but the ability to hold and manipulate several pieces of information slowly emerges over time. Inhibitory control consists of self-control (e.g., delayed gratification, inhibiting impulsive responses) and discipline (e.g., staying on task during tedious or boring tasks) (Diamond, 2013). Cognitive flexibility consists of the ability to switch strategies for a problem when facing new rules, priorities, or demands (Diamond, 2013). Development of cognitive flexibility relies on existing working memory and inhibitory control since switching strategies requires first inhibiting the previous strategy, then using working memory to hold a new strategy in mind (Diamond, 2013). Self-regulation is a component of inhibitory control with much overlap with self-control (Diamond, 2016), but self-regulation can also be considered as a part of social-emotional development. Numerous health and quality of life indicators have been shown to be associated with executive functions (Diamond, 2016). One seminal paper in particular found that children from ages 3-11 years with lower inhibitory control were more likely to be overweight, struggle with addiction, earn less, commit crimes, and be less happy as adults aged 32 years, compared to children with higher inhibitory control, while controlling for IQ, gender, social class, and family and home lives (Moffitt et al., 2011).

2.3.1.3 Social-emotional development

Social-emotional development can be considered as a preschool-aged child's emerging capacity to experience, manage, and convey the gamut of positive and negative emotions, as well as develop satisfying and close relationships with others (e.g., parents, peers) (Cohen et al., 2005). Favourable associations have been demonstrated between social-emotional development in kindergarten children and academic, employment, substance use, criminality, and mental health outcomes at approximately age 25 (Jones, Greenberg, & Crowley, 2015). A recent review categorized social-emotional development into four domains: emotional competence, social competence, behaviour problems, and self-regulation (Halle & Darling-Churchill, 2016).

2.3.1.3.1 Emotional competence

Emotional competence can broadly be thought of as the ability to comprehend one's own emotions and the emotions of others (Saarni, 1999). More specifically, emotional competence includes self -awareness, -expression, and -regulation of one's own emotional states; understanding, empathizing, and reacting to others' emotional states; and understanding the impact emotional expressiveness has on others (Saarni, 1999).

2.3.1.3.2 Social competence

While specific definitions vary, consensus exists for the broad definition of social competence as the ability of a child to successfully engage in social interactions with others (Fabes, Gaertner, & Popp, 2006). Two aspects of social competence that can indicate successful engagement in social interactions include sociability (level of participation in social interactions) and prosocial behaviour (engagement in positive social interactions) (Denham, 2006).

2.3.1.3.3 Behaviour problems

Social behaviours are considered problematic when they hinder a child's ability to function within their social contexts (e.g., home, child care) (Campbell, 1998). Two sets of problematic behaviour categories include internalizing (e.g., anxiety, social withdrawal) and externalizing (e.g., aggression, defiance) behaviours or emotions (Halle & Darling-Churchill, 2016).

2.3.1.3.4 Self-regulation

As discussed in section 2.3.1.2.2, self-regulation is a component of inhibitory control tasked with focusing attention. For social-emotional development the concept of self-regulation can be considered as the ability to manage emotions, and behaviours (Halle & Darling-Churchill, 2016). Further, self-regulation can be thought of as the ability to limit the reaction one has to a stimulus, which allows one to: not lose focus on a cognitive task, explore the full range of emotional possibilities instead of the first emotional reaction, and negotiate or resolve social interactions where the wants of the child conflict with the wants of the other (Halle & Darling-Churchill, 2016).

2.3.2 Measuring development

2.3.2.1 Physical development

A child's expected adult height can be most accurately predicted from their height when they are between the preschool and puberty age ranges (Cole & Wright, 2011).While a preschool aged child's height can predict adult height, it is important to also consider the heritability of height. For instance, heritability was found to explain 43% of the variance in height in 5 year old children (Dubois et al., 2012). For this reason, formulas that predict a child's expected adult height by considering both their current height for age and sex, as well as their biological parent's height have been proposed (Luo, Albertsson-Wikland, & Karlberg, 1998a).

Unlike height, which is a straight-forward measurement of standing length, numerous methods exist to measure adiposity. Measuring or estimating adiposity in the body can be performed through dual energy X-ray absorptiometry, densitometry, peripheral quantitative computed tomography, and multicomponent models (Lohman, Hingle, & Going, 2013). However, these lab-based methods are often not feasible in field-based settings (Reilly, 2010). As Reilly (2006) proposed, an indirect or proxy measure of adiposity is needed for field-based settings that can identify those with: an increased risk of disease arising from their adiposity levels, and the highest proportions of adipose tissue according to well-established reference data. One method proposed by Reilly (2006) was body mass index (BMI= weight [kg] / height^2 [m^2]).

Body mass index is commonly used to classify adults as overweight or obese, as adults have relatively stable height, so the changes in BMI are assumed to reflect weight gain or adiposity accumulation (relative to their existing height). However, children's height and weight undergo many stages of rapid growth, making the adult BMI classifications a poor predictor of adiposity. Thus, reference data have been used to create distribution curves adjusted for age and sex indicating a child's BMI relative to a large sample of children at similar developmental stages. The two most common international standards are from the World Health Organization (WHO) and the International Obesity Task Force (IOTF) (Cole, Flegal, Nicholls, & Jackson, 2007) (WHO, 2006; de Onis et al., 2007). However, within Canada the WHO standards are the recommended classification system (Secker, 2010).

A recent systematic review examined existing tools to measure gross motor skills (Griffiths, Toovey, Morgan, & Spittle, 2018). Tools were included in the review if they were: *"(1)discriminative, predictive or evaluative of gross motor skills, (2) assessed ≥two gross motor (eg, balance, jumping, etc) items, (3) able to extract a meaningful gross motor subscore, (4)* *applicable to children aged 2–12 years, (5) criterion or norm referenced test with a standardised assessment procedure and (6) instructional manuals are published or commercially available".* Authors found seven gross motor skill assessment tools that met this inclusion criteria. The Test of Gross Motor Development-2 (TGMD-2) was the only process-oriented tool, meaning that it measured the quality of movements as opposed to product-oriented tools that measure an outcome. For instance, in a process-oriented tool children could be assessed by their ability to coordinate their arms during running, while a product-oriented tool could assess how fast they ran (Lubans, Morgan, Cliff, Barnett, & Okely, 2010). The TGMD-2 along with the McCarron Assessment of Neuromuscular Development also had the shortest administration time at 15-20 minutes, compared to 20-60 minutes with the other tools (Griffiths et al., 2018). The TGMD-2 was found to have the most studies assessing validity and reliability. For instance, when compared to other motor development assessments the TGMD-2 demonstrated moderate-strong criterion validity (e.g., r: 0.49-0.63) (Griffiths et al., 2018). Furthermore, the TGMD-2 was shown to have the highest reliability of the studies reporting inter- and intra-rater reliability (Griffiths et al., 2018). Thus, the TGMD-2 could be considered an appropriate tool to measure gross motor skills in preschool-aged children.

2.3.2.2 Cognitive development

Numerous tools exist to measure components of cognitive development. However, it has been argued that many of these measures are not feasible in field settings, developmentally inappropriate, and are not sufficiently engaging to maintain the attention of a preschool-aged child (Howard & Melhuish, 2017). The NIH toolbox is one battery of tests that overcomes some of these limitations, since it can be administered through a tablet (Zelazo et al., 2013), however it requires an internet connection and some feel it has insufficient stimulation to maintain the attention of a preschool-aged child (Howard & Okely, 2015). More recently, an iPad application called the Early Years Toolbox, which measures components of cognitive development in early years children was created that improves upon the NIH toolbox (Howard & Melhuish, 2017). Collecting data via a portable iPad application ensures feasibility in field settings as no internet connection is required (Howard & Melhuish, 2017). Specifically, data is collected offline and when an internet connection is available data are downloaded to a secure database. Additionally, the tests are brief (≤ 5 minutes) and engaging (e.g., cartoon characters, interactive audio and visual stimuli) to maintain a young child's limited attention span (Howard & Melhuish, 2017; Howard & Okely, 2015).

The main cognitive development domains tested in the Early Years Toolbox include executive functions (i.e., visuo-spatial and phonological working memory, response inhibition, and shifting/cognitive flexibility) and language development (Howard & Melhuish, 2017). Importantly, the Early Years Toolbox has demonstrated good psychometric properties in a sample of 1,764 children (n=1,764 children aged 3.0-5.9 for visuo-spatial working memory, response inhibition, and shifting/cognitive flexibility; n=1,095 children aged 3.0-5.9 for phonological working memory; n=1,261 children aged 2.5-5.9 language development) (Howard & Melhuish, 2017). More specifically, reliability was considered good to excellent (Cronbach alpha: 0.84-0.95) when internal consistency was calculated for the response inhibition and language development measures; though no reliability values were calculated for the shifting and working memory tasks. Convergent validity was calculated with a subsample (n = 86) of participants to complete both the Early Years Toolbox and similar tasks from the NIH Toolbox and British Abilities Scales (BAS) that would be considered the norm in this age range. All Early Years Toolbox cognitive measures were moderately-strongly and significantly correlated (r=0.40

to 0.60, $p < 0.001$) when compared to their counterparts (i.e., NIH Toolbox's working memory, inhibition, and shifting tasks; BAS vocabulary task). Based on the demonstrated reliability and validity, the Early Years Toolbox appears to be an appropriate tool for future research to collect field-based measures of cognitive development in preschool-aged children.

2.3.2.3 Social-emotional development

The Early Years Toolbox (Section 2.3.3.2) also contains measures of social-emotional development in the Child Self-Regulation and Behaviour Questionnaire (CSBQ). The aspects of social-emotional development tested in the Early Years Toolbox include self-regulation (i.e., cognitive, emotional and behavioural), and social development (i.e., internalizing, externalizing, sociability, and prosocial behaviour) (Howard & Melhuish, 2017). The Early Years Toolbox demonstrated good psychometric properties in a sample of 414 children aged 3.0-5.9 for the CSBQ (Howard & Melhuish, 2017). More specifically, reliability was considered acceptable to very good when internal consistency was calculated for the CSBQ subscales of internalizing (α =0.78), externalizing (α =0.88), sociability (α =0.74), prosocial behaviour (α =0.89), as well as behavioural (α = 0.89), cognitive (α =0.87), and emotional (α =0.83) self-regulation. Additionally, convergent validity was assessed by comparing the CSBQ to the Strengths and Difficulties Questionnaire (SDQ). Since the CSBQ and the SDQ produce some of the same subscales and some different (but similar) subscales, comparisons were made directly or with a "nearest-comparison". For direct comparisons, subscales of externalizing, internalizing, prosocial behaviour were significantly and strongly to very strongly correlated (r=0.78 to 0.91, $p < 0.001$). Moderate to very strong correlations (r=0.48 to -0.81, $p < 0.001$) were also determined for nearest-comparisons between CSBQ and SDQ subdomains of sociability with prosocial behaviour, and self-regulation with hyperactivity. Based on the demonstrated reliability and validity, the Early Years Toolbox also appears to be an appropriate tool for future research to collect measures of social-emotional development in preschool-aged children.

2.3.3 Relationships between movement behaviours and health indicators

As mentioned in Section 2.3.1, four systematic reviews of the relationships between sleep, sedentary behaviour, physical activity, and combinations of more than one movement behaviours with health indicators in the early years were recently conducted. High-level results for the three individual movement behaviour reviews for each category of development (i.e., physical, cognitive, emotional/social development) are shown in Table 2.1 with trends highlighted when ≥60% of studies showed similar associations.

Table 2.1: Overview of Individual Movement Behaviour Systematic Reviews

	Sleep[1]			Sedentary Behaviour[2]			Physical Activity[3]		
	F	U	N	F	U	N	F	U	N
Physical Development	**24***	2	12	4	41	**75***	47	7	40
Adiposity	**20***	2	9	3	35	**64***	18	4	30
Motor development	0	0	**2***	1	4	**8***	**18***	1	3
Growth	**2***	0	0	ns	ns	ns	ns	ns	ns
Risk/Injuries	**2***	0	1	0	0	0	1	1	1
Bone and Skeletal Health	ns	ns	ns	0	0	**2***	**5***	0	2
Cardiometabolic health	0	0	0	0	0	**1***	2	1	4
Fitness	ns	ns	ns	0	**2***	0	**3***	0	0
Social-Emotional Development	13	2	11	2	11	13	5	3	3
Emotional regulation	13	2	10	ns	ns	ns	ns	ns	ns
Quality of life/well-being	0	0	**1***	ns	ns	ns	ns	ns	ns
Psychosocial health	ns	ns	ns	2	11	13	**5**	3	3
Cognitive Development	6	2	8	6	15	18	**10***	2	1
Cognitive Development	6	2	8	6	15	18	**10***	2	1

F = number of favourably associated studies; U = number of unfavourably associated studies; N = number of null associated studies; ns = indicator not searched for in that review; [1] = Numbers listed represents number of studies; [2] = Numbers listed represents the number of reported associations; [3] = Numbers listed represents number of studies, studies with mixed findings were also found but not included in this table; * and bolded values show ≥60% consistency

Overall, sleep was favorably associated with physical development and no consistent trends were seen for social-emotional and cognitive development (Chaput et al., 2017c). More specifically, sleep was favourably associated with adiposity, growth, and risk/injuries, and not associated with motor development and quality of life. For the other health indicators, no consistent trends were seen with sleep. Most sleep studies assessed physical development, while the least amount of studies assessed cognitive development.

Overall, sedentary behaviour was not associated with physical development, and no consistent trends were seen for social-emotional and cognitive development (Poitras et al., 2017). More specifically, sedentary behaviour was unfavourably associated with fitness, and not associated with adiposity, motor development, bone and skeletal health, and cardiometabolic health. Since a main conclusion from this review was that sedentary behaviours should be contextually examined, consistency was also assessed for objectively measured sedentary time, screen time, and reading. Objectively measured sedentary time was not associated with adiposity, motor development, bone and skeletal health, psychosocial health, and cognitive development. Screen time was unfavourably associated with fitness, but not associated with motor development, bone and skeletal health, and cardiometabolic health. As well, reading was favourably associated with cognitive development, but not associated with adiposity. For the other health indicators, no consistent trends were seen with sedentary behaviour. Most sedentary behaviour studies assessed physical development, while the fewest studies were found for social-emotional development.

Overall, physical activity was positively associated with cognitive development but no consistent trends were seen for physical and social-emotional development (Carson et al., 2017c). When considering specific health indicators, physical activity was favourably associated with motor development, bone and skeletal health, fitness, and cognitive development. For the other indicators, no consistent trends were seen with physical activity. Most physical activity studies assessed physical development, while the least amount of studies examined social-emotional development.

Based on the three systematic reviews that examined the association between movement behaviours and health indicators in isolation, it could be concluded that movement behaviours are related to physical and cognitive development, while no consistent trends were seen for social-emotional development. Most evidence existed for physical development, with nearly twice as many studies compared to cognitive and social-emotional development combined. Based on these findings, more research is needed across all domains of movement behaviours and development. However, it is important to note that these conclusions are based on a segregated not integrated approach; whereas the fourth review took an integrated approach.

In the integrated review the term ideal combinations was operationalized as any combination of movement behaviour hypothesized to be beneficial for health, based on older populations (e.g., high sleep, low sedentary behaviour, and high physical activity; increased sleep, decreased sedentary behaviour, increased physical activity; sedentary behaviour replaced with physical activity). Ideal combinations of sedentary behaviour and physical activity did not demonstrate consistent trends with physical development. More specifically, ideal combinations of sedentary behaviour and physical activity were favourably associated with motor development and fitness, but not associated with adiposity and growth. Additionally, ideal combinations of sleep and sedentary behaviour were favorably associated with physical development, but the only indicator for this combination was adiposity.

From the 10 studies included in the integrated review, several main gaps in the literature were identified. First, most combinations of movement behaviours were sedentary behaviour and physical activity, with limited information on other combinations of movement behaviours.

Second, adiposity was the most studied health indicator, and no studies were found examining combinations of movement behaviours and cognitive or social-emotional development. Finally, studies using compositional data analyses to examine the relationships between movement behaviours and health indicators were not found.

Since the integrated movement behaviour systematic review (Kuzik et al., 2017), two studies have used compositional analyses to examine the associations between all movement behaviours and physical development outcomes in preschool aged children (Carson et al., 2017d; Taylor et al., 2018). For instance, in a nationally representative sample of 552 Canadian preschool age children the overall composition of movement behaviours was associated with BMI z-scores but not waist circumference (Carson et al., 2017d). However, individual movement behaviours, relative to the other movement behaviours, did not demonstrate any significant associations (Carson et al., 2017d). In another study using compositional substitution analyses, adding sleep and subtracting both LPA and stationary time were favourably associated with BMI z-scores at 3.5 years of age in a sample of 380 children from New Zealand (Taylor et al., 2018). However, neither study examined cognitive or social-emotional development indicators. Thus, an area of high importance would be the examination of the associations between all movement behaviours and physical, cognitive, and social-emotional development using these novel statistical techniques.

2.4 <u>Time-use compositions</u>

2.4.1 <u>Prevalences</u>

Measuring the prevalence of movement behaviours in preschool-aged children is essential for determining whether interventions and initiatives are needed that attempt to alter the levels of movement behaviours. Additionally, Pedišić et al. (2017) noted that the prevalence of movement behaviours is typically reported as arithmetic means or medians, suggesting that compositional means would be more appropriate. In line with this suggestion (Carson et al., 2017d) recently calculated the compositional means of movement behaviours using a representative dataset of Canadians. Accordingly, Canadian preschoolers spent 7.4 hours/day (30.9% of day) engaged in stationary time, 3.8 hours/day (15.9% of day) engaged in LPA, 1.1 hours/day (4.5% of day) engaged in MVPA, and 11.7 hours/day (48.7% of day) engaged in sleep (Carson et al., 2017d).

In addition to calculating compositional means for a representative sample of early years children another useful measure of prevalence is the proportion of children meeting movement behaviour guidelines. The *Canadian 24-Hour Movement Guidelines for the Early Years* have recently been created and suggest levels of movement behaviours for infants, toddlers, and preschoolers (see Table 2.2) (Tremblay et al., 2017b). Internationally, adherence to 24-Hour Movement Behaviour Guidelines estimates range from 5-24% for meeting all recommendations (Berglind, Ljung, Tynelius, & Brooke, 2018; Carson et al., 2019; Chaput et al., 2017a; Cliff et al., 2017; De Craemer, McGregor, Androutsos, Manios, & Cardon, 2018; Guan et al., 2020; Hinkley et al., 2020; Leppänen et al., 2019). Based on a nationally representative Canadian sample (i.e., CHMS), only 13% of preschool aged children meet the overall guidelines (Chaput et al., 2017a). Additionally, the prevalence of children meeting individual guidelines were: 84% for sleep, 24% for screen time, and 62% for physical activity (Chaput et al., 2017a).

Table 2.2: Canadian 24-Hour Movement Guidelines for the Early Years

	Infants (0.0-11.9 months)	**Toddlers (12.0-35.9 months)**	**Preschoolers (36.0-59.9 months)**

Sleep	• 14-17 hours (0-3 months) • 12-16 hours (4-11 months)	• 11-14 hours	• 10-13 hours/day
Sedentary Behaviour	• ≤ 60 minutes/day restrained time • No screen time	• ≤ 60 minutes/day restrained time • No screen time <24 months • ≤1 hour/day screen time >24 months	• ≤ 60 minutes/day restrained time • ≤1 hour/day screen time
Physical Activity	• >30 minutes/day tummy time	• ≥180 minutes/day TPA	• ≥180 minutes/day TPA • ≥ 60 minutes/day MVPA

TPA = Total physical activity; MVPA = Moderate-to-vigorous physical activity

2.5 Determinants and correlates of optimal time-use

2.5.1 Domains of correlates

Socio-ecological models have guided the identification of relevant correlates and determinants of sleep (El-Sheikh & Sadeh, 2015), sedentary behaviour (Owen et al., 2011), and physical activity (Sallis et al., 2015; Spence & Lee, 2003). To conceptualize correlates of sleep in children, a systems model was created by El-Sheihk and Sadeh (2015) based on the Bronfenbrenner (1979) ecological systems model and the transactional (systems) model of development (Sameroff, 1975). The different correlates of sleep are said to be influenced by the child (e.g., temperament, maturation, genetics), the immediate context (e.g., sleep conditions, parenting, light-dark cycle), social context (e.g., school factors, social life), and cultural context (e.g., beliefs about sleep, co-sleeping). To conceptualize correlates of physical activity, Sallis et al. (2015) discussed several historical and contemporary ecological models, including Bronfenbrenner's model (Bronfenbrenner, 1979). Sallis et al. (2015) further discuss the core concepts of each model by identifying key levels of influence: intrapersonal (biological, psychological), interpersonal (social, cultural), organizational, community, physical environment, and policy. Salmon, Tremblay, Marshall, and Hume (2011) also conceptualized sedentary behaviour correlates within an ecologic framework and identified correlates of sedentary behaviours at the level of individual, social, and physical environmental influences. Lastly, the VIRTUE framework discusses the need for future research to identify correlates and determinants of movement behaviour compositions. Correlates and determinants in the interpersonal level of the ecological framework are thought to be especially influential to children's behaviours based on the large role parents play in children's development (Welk, Wood, & Morss, 2003).

2.5.2 Parental correlates

According to the Socialization Model of Child Behaviour, parental behaviours directly influence children's behaviours (Taylor, Baranowski, & Sallis, 1994) , especially in early years children who have limited autonomy from their parents (Vaughn, Hales, & Ward, 2013). This is intuitive since parents control access to many movement behaviour opportunities. For sleep, Dahl (1996) stressed the importance of the need to feel a sense of physical and emotional safety to reach a sleep state. The importance of the family unit is thus highlighted considering this sense of physical and emotional safety in early years children is in large part shaped by the parent-child relationship and the environment the child sleeps in is provided by the parent (Bowlby 1992; Cummings and Davies 1996). For physical activity and sedentary behaviour the role of the parent has been extensively studied in children of all ages. This is evident by the numerous systematic reviews and reviews of reviews on the topic of parental influences of physical activity and sedentary behaviour. (Bauman et al., 2012; Beets, Cardinal, & Alderman, 2010; Biddle, Atkin, Cavill, & Foster, 2011; Biddle, Whitehead, O'Donovan, & Nevill, 2005; Craggs, Corder, Sluijs, & Griffin, 2011; Edwardson & Gorely, 2010; Gustafson & Rhodes, 2006; Horst, Paw, Twisk, & Mechelen, 2007; Mendonça, Cheng, Mélo, & Farias Júnior, 2014; Pugliese & Tinsley, 2007; Sallis, Prochaska, & Taylor, 2000; Sluijs, Kriemler, & McMinn, 2011; Sluijs, McMinn, & Griffin, 2007; Sterdt, Liersch, & Walter, 2013; Trost & Loprinzi, 2011; Webber & Loescher, 2013). The influence a parent exerts on a child's movement behaviours is studied through several concepts (e.g., parental modeling, house rules). One concept that may be applicable to all movement behaviours is parental modeling.

2.5.2.1 Parental modeling

Parental modeling is a well-endorsed possible mechanism for parent-child aggregation of health behaviours (Davison et al., 2013; Taylor et al., 1994; Trost & Loprinzi, 2011; Yao & Rhodes, 2015). Bandura (1986) differentiated five modeling phenomena within Social Cognitive Theory. It could be argued that the main types of parental modeling influential to children's movement behaviours are observational learning effects and response facilitation effects. Observational learning effects require a novel behaviour to be observed and reproduced by the observer. Thus, observational learning could explain more complicated behaviours (e.g., dribbling a basketball) but may not explain the more commonly occurring movement behaviours (e.g., sleeping).

Response facilitation effects occur when a modeled behaviour acts as a social prompt for the observer to perform a behaviour that has been previously learned and is currently not being performed due to lack of motivation—not inhibition. The mechanism for the majority of parental modelling on children's movement behaviours may then fall more into response facilitation effects. As said by Bandura (1986) in regards to response facilitation " *…the types of models that prevail within a social milieu partly determine which qualities, from among many alternatives, are selectively activated*". This statement further demonstrates the significance of parental influence, considering the limited number of models early years children are exposed to and the role of parents in cultivating the social environment of the home.

The role of parental modeling in children's movement behaviours has predominantly been studied in the areas of physical activity and sedentary behaviour (Davison et al., 2013; Trost & Loprinzi, 2011; Yao & Rhodes, 2015). For physical activity and sedentary behaviour, parental modeling has typically been operationalized as the association between parents' and children's levels of physical activity and/or sedentary behaviour (Yao & Rhodes, 2015), which could also be explored for levels of sleep. Other operationalization's of parental modeling include co-participation (e.g., how often the parent engages in physical activity with the child) and frequency of observed behaviour (e.g., how often the child sees the parent engaging in physical activity) (Davison et al., 2013; Gattshall, Shoup, Marshall, Crane, & Estabrooks, 2008; Østbye et al., 2013). The frequency a child views a parent sleep could intuitively have limited explanative capacity, since a child would typically already be sleeping when a parent is sleeping. However, the co-activity of sleep (i.e., co-sleeping, or bed-sharing and room-sharing with the child) is a highly studied and controversial research topic.

2.5.2.1.1 Sleep

Co-sleeping is a contested issue. Sleeping in direct proximity of parents has historically, and biologically been the norm, as a means of providing children with warmth, nutrition, and protection (Thoman, 2006). Shifting from nomadic cultures to cultures with permanent dwellings moved co-sleeping from a necessity to a choice, and over the past two centuries co-sleeping has further decreased as industrialization has made child-specific bedding more easily available (Thoman, 2006). While co-sleeping has vastly decreased in popularity in Western countries, it cannot be considered the global norm. Contemporary cultural differences exist as co-sleeping is highly prevalent in predominantly Asian countries compared to pre-dominantly Caucasian countries for early years children (Mindell, Sadeh, Kwon, & Goh, 2013; Mindell, Sadeh, Wiegand, How, & Goh, 2010). The debate was polarized in the 1990's as public health campaigns recommended against co-sleeping to reduce sudden infant death syndrome (SIDS) (Hardy Havens & Zink, 1994); though, some feel the association between co-sleeping and SIDS is also polarized in the literature, with no definitive proof on either side of the argument (Mileva-Seitz, Bakermans-Kranenburg, Battaini, & Luijk, 2017). It is for this reason that Mileva-Seitz et al. (2017) urge future research to examine how parent-child proximity influences children's sleep and subsequent development. For early years children, co-sleeping appears to be associated with lower sleep compared to solitary sleep (Huang et al., 2016; Hysing et al., 2014; Mindell et al., 2013; Mindell et al., 2010; Touchette et al., 2009). Considering parental sleep duration and child sleep duration needs are vastly different, this could represent a downside to parental modeling as children regress towards parental sleep levels. Alternatively, since these studies were parent-report measures, and parent-report sleep more accurately predicts time sent to bed not time sleeping (Dayyat, Spruyt, Molfese, & Gozal, 2011), this may reflect parents that co-sleep having more accurate estimates of children's sleep patterns.

2.5.2.1.2 Sedentary behaviour

While the examination of parental modeling of screen time has frequently been studied, less research has been conducted with objectively measure stationary time. Considering Downing, Hinkley, Salmon, Hnatiuk, and Hesketh (2017) found few common correlates between screen time and sedentary time, generalizations from the screen time literature could be problematic. Of the studies measuring sedentary time in early years children, only one study was found that examined parental modeling correlates of sedentary time where the correlates were specific to sedentary behaviour; however, no significant associations were observed (Downing et al., 2017). Other studies have examined physical activity specific modeling correlates and no significant relationships with early years sedentary time were found (Byun, Dowda, & Pate, 2011; Dolinsky, Brouwer, Østbye, Evenson, & Siega-Riz, 2011; Østbye et al., 2013). No significant associations were found between parent-child levels of sedentary behaviour when parental sedentary behaviour was questionnaire derived (Dolinsky et al., 2011; Schmutz et al., 2017), however significant associations have been found between objectively measured parental sedentary time and children's sedentary time (Carson, Langlois, & Colley, 2020; Garriguet, Colley, & Bushnik, 2017; Hesketh et al., 2014; Hughes, Muggeridge, Gibson, Johnstone, & Kirk, 2016; Ruiz, Gesell, Buchowski, Lambert, & Barkin, 2011).

2.5.2.1.3 Physical activity

A systematic review of correlates and determinants of physical activity in early years children found that parent and child's levels of physical activity were not related (Bingham et al., 2016b). However, within a nationally representative Canadian sample, parents total LPA and MVPA was associated with preschool-aged children's total LPA and MVPA (Carson et al., 2020). Further, positive relationships have been demonstrated between time spent playing with parents and children's total physical activity (Bingham et al., 2016b). Some have proposed the inconsistent relationships between parent and children's physical activity are attenuated by the current use of subjective measurements (Rhodes & Quinlan, 2014). Objective measurement of parent and child physical activity and co-participation could help further explore these relationships.

2.5.2.2 Measurement

A better understanding of the influence that parent modeling has on movement behaviours has been highlighted in the research. To achieve this goal, the need for an objective measure of parent-child proximity during movement behaviours has been identified as a research priority (Davison et al., 2013; Mâsse & Watts, 2013; Mileva-Seitz et al., 2017; Rhodes & Quinlan, 2014; Trost & Loprinzi, 2011). Using ActiGraph accelerometers, Kuzik and Carson (2018) validated a new Bluetooth feature as an estimate of presence or absence of close-proximity between a parent and early years child. Accelerometers were worn by a parent and a child 24 hours/day for 7 days. Along with objective measures of movement, Bluetooth signals were emitted by one accelerometer and recorded by the other. Using parental log-sheets in 5-minute epochs as the ground truth measure, accelerometer-derived parent-child proximity demonstrated good concurrent validity (receiver operating characteristic (ROC) area under the curve (AUC): 0.84; 95% confidence intervals: 0.84, 0.85). Thus, using this Bluetooth feature in ActiGraph WGT3X-BT accelerometers could allow future research to determine how parent-child proximity influences early years children's movement behaviours.

2.6 References

Acebo, C., Sadeh, A., Seifer, R., Tzischinsky, O., Wolfson, A. R., Hafer, A., & Carskadon, M. A. (1999). Estimating sleep patterns with activity monitoring in children and adolescents: How many nights are necessary for reliable measures? *Sleep, 22*(1), 95-103.

ActiGraph Support Center. (2014). What is proximity tagging and how does it work? Retrieved from https://actigraph.desk.com/customer/en/portal/articles/2515795-what-is-proximity-tagging-and-how-does-it-work-

ActiGraph Support Center. (2016). Lux measurements. Retrieved from https://actigraph.desk.com/customer/en/portal/articles/2515504-lux-measurements

ActiGraph Support Center. (2017a). ActiGraph white paper. Estimating human position with the ActiGraph GT3X triaxial activity monitor. Retrieved from http://actigraphcorp.com/wp-content/uploads/2015/06/Inclination-White-Paper.pdf

ActiGraph Support Center. (2017b). Where can I find documentation for the Sadeh and Cole-Kripke algorithms? Retrieved from https://actigraph.desk.com/customer/en/portal/articles/2515585-where-can-i-find-documentation-for-the-sadeh-and-cole-kripke-algorithms-

Addy, C. L., Trilk, J. L., Dowda, M., Byun, W., & Pate, R. R. (2014). Assessing preschool children's physical activity: How many days of accelerometry measurement. *Pediatric Exercise Science, 26*(1), 103-109. doi:10.1123/pes.2013-0021

Aitchison, J. (1986). *The statistical analysis of compositional data*: Chapman & Hall, Ltd.

Alhassan, S., Sirard, J. R., Kurdziel, L. B. F., Merrigan, S., Greever, C., & Spencer, R. M. C. (2017). Cross-Validation of Two Accelerometers for Assessment of Physical Activity and Sedentary Time in Preschool Children. *Pediatric Exercise Science, 29*(2), 268-277. doi:https://dx.doi.org/10.1123/pes.2016-0074

Bandura, A. (1986). Social foundations of thought and action : A social cognitive theory. Englewood Cliffs, N.J.: Prentice-Hall.

Barreira, T. V., Schuna, J. M., Mire, E. F., Katzmarzyk, P. T., Chaput, J. P., Leduc, G., & Tudor-Locke, C. (2015). Identifying children's nocturnal sleep using 24-h waist accelerometry. *Medicine & Science in Sports & Exercise, 47*(5), 937-943. doi:https://dx.doi.org/10.1249/MSS.0000000000000486

Batty, G. D., Shipley, M. J., Gunnell, D., Huxley, R., Kivimaki, M., Woodward, M., . . . Smith, G. D. (2009). Height, wealth, and health: An overview with new data from three longitudinal studies. *Economics & Human Biology, 7*(2), 137-152. doi:https://doi.org/10.1016/j.ehb.2009.06.004

Bauman, A. E., Reis, R. S., Sallis, J. F., Wells, J. C., Loos, R. J. F., & Martin, B. W. (2012). Correlates of physical activity: Why are some people physically active and others not? *The Lancet, 380*(9838), 258-271.

Beets, M. W., Cardinal, B. J., & Alderman, B. L. (2010). Parental social support and the physical activity-related behaviors of youth: A review. *Health Education & Behavior, 37*(5), 621-644.

Berglind, D., Ljung, R., Tynelius, P., & Brooke, H. L. (2018). Cross-sectional and prospective associations of meeting 24-h movement guidelines with overweight and obesity in preschool children. *Pediatric Obesity, 13*(7), 442-449. doi:10.1111/ijpo.12265

Berk, L. E. (2013). *Development through the lifespan* (6 ed.). Boston, MA: Pearson.

Biddle, S. J. H., Atkin, A. J., Cavill, N., & Foster, C. (2011). Correlates of physical activity in youth: A review of quantitative systematic reviews. *International Review of Sport and Exercise Psychology, 4*(1), 25-49.

Biddle, S. J. H., Whitehead, S. H., O'Donovan, T. M., & Nevill, M. E. (2005). Correlates of participation in physical activity for adolescent girls: A systematic review of recent literature. *Journal of Physical Activity and Health, 2*(4), 423-434.

Bingham, D. D., Costa, S., Clemes, S. A., Routen, A. C., Moore, H. J., & Barber, S. E. (2016a). Accelerometer data requirements for reliable estimation of habitual physical activity and sedentary time of children during the early years-a worked example following a stepped approach. *Journal of Sports Sciences, 34*(20), 2005-2010.

Bingham, D. D., Costa, S., Hinkley, T., Shire, K. A., Clemes, S. A., & Barber, S. E. (2016b). Physical activity during the early years: A systematic review of correlates and determinants. *American Journal of Preventive Medicine, 51*(3), 384-402. doi:10.1016/j.amepre.2016.04.022

Brønd, J. C., & Arvidsson, D. (2016). Sampling frequency affects the processing of ActiGraph raw acceleration data to activity counts. *Journal of Applied Physiology, 120*(3), 362-369. doi:10.1152/japplphysiol.00628.2015

Bronfenbrenner, U. (1979). *The ecology of human development*: Harvard university press.

Byun, W., Beets, M., & Pate, R. (2015). Sedentary behavior in preschoolers: How many days of accelerometer monitoring is needed? *International Journal of Environmental Research and Public Health, 12*(10), 13148.

Byun, W., Dowda, M., & Pate, R. R. (2011). Correlates of Objectively Measured Sedentary Behavior in US Preschool Children. *Pediatrics, 128*(5), 937-945. doi:10.1542/peds.2011-0748

Campbell, S. B. (1998). Developmental perspectives *Handbook of Child Psychopathology* (pp. 3-35): Springer.

Carson, V., Ezeugwu, V. E., Tamana, S. K., Chikuma, J., Lefebvre, D. L., Azad, M. B., . . . Mandhane, P. J. (2019). Associations between meeting the Canadian 24-Hour Movement Guidelines for the Early Years and behavioral and emotional problems among 3-year-olds. *Journal of Science and Medicine in Sport, 22*(7), 797-802. doi:https://doi.org/10.1016/j.jsams.2019.01.003

Carson, V., Hunter, S., Kuzik, N., Gray, C. E., Poitras, V. J., Chaput, J.-P., . . . Connor Gorber, S. (2016). Systematic review of sedentary behaviour and health indicators in school-aged children and youth: An update. *Applied Physiology, Nutrition, and Metabolism, 41*(6), S240-S265.

Carson, V., Langlois, K., & Colley, R. (2020). Associations between parent and child sedentary behaviour and physical activity in early childhood. *Health Rep, 31*(2), 3-10. doi:10.25318/82-003-x202000200001-eng

Carson, V., Lee, E., Hewitt, L., Jennings, C., Hunter, S., Kuzik, N., . . . Tremblay, M. (2017c). Systematic review of the relationships between physical activity and health indicators in the early years (aged 0 to 4 years). *BMC Public Health, 17*(5), 854.

Carson, V., Tremblay, M., & Chastin, S. (2017d). Cross-sectional associations between sleep duration, sedentary time, physical activity and adiposity indicators among canadian preschool children using compositional analyses. *BMC Public Health, 17*(5), 848.

Chaput, J.-P., Carson, V., Gray, C. E., & Tremblay, M. S. (2014). Importance of All Movement Behaviors in a 24 Hour Period for Overall Health. *International Journal of*

Environmental Research and Public Health, 11(12), 12575-12581. doi:10.3390/ijerph111212575
Chaput, J.-P., Colley, R. C., Janssen, I., Carson, V., Roberts, K. C., Aubert, S., & Tremblay, M. (2017a). Proportion of preschool-aged children meeting the Canadian 24-Hour Movement Guidelines for the Early Years and associations with adiposity: Results from the Canadian Health Measures Survey. *BMC Public Health, 17*(5), 829.
Chaput, J.-P., Gray, C., Poitras, V., Carson, V., Gruber, R., Birken, C., . . . Tremblay, M. (2016). Systematic review of the relationships between sleep duration and health indicators in school-aged children and youth. *Applied Physiology, Nutrition, and Metabolism, 41*(6), S266-S282.
Chaput, J. P., Gray, C., Poitras, V., Carson, V., Gruber, R., Birken, C., . . . Tremblay, M. (2017c). Systematic review of the relationships between sleep duration and health indicators in children aged 0-4 years. *BMC Public Health, 17*(5), 855.
Chastin, S. F., Palarea-Albaladejo, J., Dontje, M. L., & Skelton, D. A. (2015). Combined effects of time spent in physical activity, sedentary behaviors and sleep on obesity and cardio-metabolic health markers: A novel compositional data analysis approach. *PLOS ONE, 10*(10), e0139984. doi:10.1371/journal.pone.0139984
Cliff, D. P., McNeill, J., Vella, S. A., Howard, S. J., Santos, R., Batterham, M., . . . de Rosnay, M. (2017). Adherence to 24-Hour Movement Guidelines for the Early Years and associations with social-cognitive development among Australian preschool children. *BMC Public Health, 17*(5), 857. doi:10.1186/s12889-017-4858-7
Cliff, D. P., Reilly, J. J., & Okely, A. D. (2009). Methodological considerations in using accelerometers to assess habitual physical activity in children aged 0-5 years. *Journal of Science and Medicine in Sport, 12*(5), 557-567. doi:10.1016/j.jsams.2008.10.008
Cohen, J., Onunaku, N., Clothier, S., & Poppe, J. (2005). *Helping young children succeed: Strategies to promote early childhood social and emotional development.* Paper presented at the Research and Policy Report. Washington, DC: National Conference of State Legislatures.
Cole, R. J., Kripke, D. F., Gruen, W., Mullaney, D. J., & Gillin, J. C. (1992). Automatic sleep/wake identification from wrist activity. *Sleep, 15*(5), 461-469. doi:10.1093/sleep/15.5.461
Cole, T. J., & Wright, C. M. (2011). A chart to predict adult height from a child's current height. *Annals of human biology, 38*(6), 662-668.
Colley, R. C., Harvey, A., Grattan, K. P., & Adamo, K. B. (2014). Impact of accelerometer epoch length on physical activity and sedentary behaviour outcomes for preschool-aged children. *Health Rep, 25*(1), 3.
Costa, S., Barber, S. E., Cameron, N., & Clemes, S. A. (2014). Calibration and validation of the ActiGraph GT3X+ in 2-3 year olds. *Journal of Science and Medicine in Sport, 17*(6), 617-622. doi:https://dx.doi.org/10.1016/j.jsams.2013.11.005
Cowan, N. (2008). What are the differences between long-term, short-term, and working memory? *Progress in brain research, 169*, 323-338. doi:10.1016/S0079-6123(07)00020-9
Craggs, C., Corder, K., Sluijs, E. M. F., & Griffin, S. J. (2011). Determinants of change in physical activity in children and adolescents: A systematic review. *American Journal of Preventive Medicine, 40*(6), 645-658.

Davison, K. K., Mâsse, L. C., Timperio, A., Frenn, M. D., Saunders, J., Mendoza, J. A., . . . Trost, S. G. (2013). Physical activity parenting measurement and research: Challenges, explanations, and solutions. *Childhood Obesity, 9*(s1), S-103-S-109.

Dayyat, E. A., Spruyt, K., Molfese, D. L., & Gozal, D. (2011). Sleep estimates in children: Parental versus actigraphic assessments. *Nat Sci Sleep, 3*, 115-123. doi:10.2147/nss.s25676

De Craemer, M., McGregor, D., Androutsos, O., Manios, Y., & Cardon, G. (2018). Compliance with 24-h Movement Behaviour Guidelines among Belgian Pre-School Children: The ToyBox-Study. *International Journal of Environmental Research and Public Health, 15*(10). doi:10.3390/ijerph15102171

Denham, S. A. (2006). Social-emotional competence as support for school readiness: What is it and how do we assess it? *Early Education and Development, 17*(1), 57-89.

Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*, 135-168.

Diamond, A. (2016). Why improving and assessing executive functions early in life is critical. *Executive Function in Preschool Age Children: Integrating Measurement, Neurodevelopment and Translational Research.* Washington, DC: American Psychological Association.

Doherty, A., Jackson, D., Hammerla, N., Plötz, T., Olivier, P., Granat, M. H., . . . Owen, C. G. (2017). Large scale population assessment of physical activity using wrist worn accelerometers: the UK biobank study. *PLOS ONE, 12*(2).

Dolinsky, D. H., Brouwer, R. J. N., Østbye, T., Evenson, K. R., & Siega-Riz, A. M. (2011). Peer reviewed: Correlates of sedentary time and physical activity among preschool-aged children. *Preventing Chronic Disease, 8*(6).

Downing, K. L., Hinkley, T., Salmon, J., Hnatiuk, J. A., & Hesketh, K. D. (2017). Do the correlates of screen time and sedentary time differ in preschool children? *BMC Public Health, 17*, 285. doi:10.1186/s12889-017-4195-x

Dubois, L., Ohm Kyvik, K., Girard, M., Tatone-Tokuda, F., Pérusse, D., Hjelmborg, J., . . . Martin, N. G. (2012). Genetic and environmental contributions to weight, height, and BMI from birth to 19 years of age: an international study of over 12,000 twin pairs. *PLOS ONE, 7*(2), e30153-e30153. doi:10.1371/journal.pone.0030153

Dumuid, D., Pedišić, Ž., Stanford, T. E., Martín-Fernández, J.-A., Hron, K., Maher, C. A., . . . Olds, T. (2019). The compositional isotemporal substitution model: A method for estimating changes in a health outcome for reallocation of time between sleep, physical activity and sedentary behaviour. *Statistical Methods in Medical Research, 28*(3), 846-857. doi:10.1177/0962280217737805

Dumuid, D., Stanford, T., Martin-Fernández, J., Pedišić, Ž., Maher, C., Lewis, L., . . . Olds, T. (2017). Compositional data analysis for physical activity, sedentary time and sleep research. *Statistical Methods in Medical Research, 0*(0), 0962280217710835. doi:10.1177/0962280217710835

Edwardson, C. L., & Gorely, T. (2010). Parental influences on different types and intensities of physical activity in youth: A systematic review. *Psychology of Sport and Exercise, 11*.

Edwardson, C. L., Rowlands, A. V., Bunnewell, S., Sanders, J., Esliger, D. W., Gorely, T., . . . Yates, T. (2016). Accuracy of posture allocation algorithms for thigh- and waist-worn accelerometers. *Medicine & Science in Sports & Exercise, 48*(6), 1085-1090. doi:10.1249/mss.0000000000000865

El-Sheikh, M., & Sadeh, A. (2015). Sleep and development: Introduction to the monograph. *Monographs of the Society for Research in Child Development, 80*(1), 1-14. doi:10.1111/mono.12141

Esliger, D., Copeland, J., Barnes, J., & Tremblay, M. (2005). Standardizing and optimizing the use of accelerometer data for free-living physical activity monitoring. *Journal of Physical Activity and Health, 2*(3), 366-383.

Evenson, K. R., Catellier, D. J., Gill, K., Ondrak, K. S., & McMurray, R. G. (2008). Calibration of two objective measures of physical activity for children. *Journal of Sports Sciences, 26*(14), 1557-1565.

Fabes, R. A., Gaertner, B. M., & Popp, T. K. (2006). Getting along with others: Social competence in early childhood. *Blackwell Handbook of Early Childhood Development*, 296-316.

Fenson, L., Dale, P. S., Reznick, J. S., Bates, E., Thal, D. J., Pethick, S. J., . . . Stiles, J. (1994). Variability in early communicative development. *Monographs of the Society for Research in Child Development, 59*(5), i-185. doi:10.2307/1166093

Filzmoser, P., Hron, K., & Templ, M. (2018). Applied compositional data analysis (pp. 181-205). Switzerland: Springer Nature.

Flynn, J. I., Coe, D. P., Larsen, C. A., Rider, B. C., Conger, S. A., & Bassett Jr, D. R. (2014). Detecting indoor and outdoor environments using the ActiGraph GT3X+ light sensor in children. *Medicine & Science in Sports & Exercise, 46*(1), 201-206.

Galland, B., Meredith-Jones, K., Terrill, P., & Taylor, R. (2014a). Challenges and emerging technologies within the field of pediatric actigraphy. *Frontiers in Psychiatry Frontiers Research Foundation, 5*, 99. doi:https://dx.doi.org/10.3389/fpsyt.2014.00099

Galland, B. C., Kennedy, G. J., Mitchell, E. A., & Taylor, B. J. (2012). Algorithms for using an activity-based accelerometer for identification of infant sleep-wake states during nap studies. *Sleep Medicine, 13*(6), 743-751. doi:10.1016/j.sleep.2012.01.018

Galland, B. C., Meredith-Jones, K., Gray, A., Sayers, R., Lawrence, J., Taylor, B., & Taylor, R. (2016). Criteria for nap identification in infants and young children using 24-h actigraphy and agreement with parental diary. *Sleep Medicine, 19*, 85-92. doi:https://dx.doi.org/10.1016/j.sleep.2015.10.013

Garriguet, D., Colley, R., & Bushnik, T. (2017). Parent-Child association in physical activity and sedentary behaviour. *Health Rep, 28*(6), 3.

Gattshall, M. L., Shoup, J. A., Marshall, J. A., Crane, L. A., & Estabrooks, P. A. (2008). Validation of a survey instrument to assess home environments for physical activity and healthy eating in overweight children. *International Journal of Behavioral Nutrition and Physical Activity, 5*(1), 3. doi:10.1186/1479-5868-5-3

Geserick, M., Vogel, M., Gausche, R., Lipek, T., Spielau, U., Keller, E., . . . Körner, A. (2018). Acceleration of BMI in early childhood and risk of sustained obesity. *New England Journal of Medicine*.

Gooch, D., Thompson, P., Nash, H. M., Snowling, M. J., & Hulme, C. (2016). The development of executive function and language skills in the early school years. *Journal of Child Psychology and Psychiatry, 57*(2), 180-187. doi:10.1111/jcpp.12458

Goodlin-Jones, B. L., Sitnick, S. L., Tang, K., Liu, J., & Anders, T. F. (2008). The children's sleep habits questionnaire in toddlers and preschool children. *Journal of Developmental and Behavioral Pediatrics, 29*(2), 82-88.

Griffiths, A., Toovey, R., Morgan, P. E., & Spittle, A. J. (2018). Psychometric properties of gross motor assessment tools for children: a systematic review. *BMJ Open, 8*(10), e021734. doi:10.1136/bmjopen-2018-021734

Guan, H., Zhang, Z., Wang, B., Okely, A. D., Tong, M., Wu, J., & Zhang, T. (2020). Proportion of kindergarten children meeting the WHO guidelines on physical activity, sedentary behaviour and sleep and associations with adiposity in urban Beijing. *BMC Pediatrics, 20*(1), 70. doi:10.1186/s12887-020-1969-6

Gustafson, S. L., & Rhodes, R. E. (2006). Parental correlates of physical activity in children and early adolescents. *Sports Medicine, 36*.

Halle, T. G., & Darling-Churchill, K. E. (2016). Review of measures of social and emotional development. *Journal of Applied Developmental Psychology, 45*(Supplement C), 8-18. doi:https://doi.org/10.1016/j.appdev.2016.02.003

Hardy Havens, D., & Zink, R. L. (1994). The "back to sleep" campaign. *Journal of Pediatric Health Care, 8*(5), 240-242. doi:http://dx.doi.org/10.1016/0891-5245(94)90070-1

Hesketh, K. R., Goodfellow, L., Ekelund, U., McMinn, A. M., Godfrey, K. M., Inskip, H. M., . . . van Sluijs, E. M. (2014). Activity levels in mothers and their preschool children. *Pediatrics, 133*(4), e973-980. doi:http://dx.doi.org/10.1542/peds.2013-3153

Hidding, L. M., Altenburg, T. M., Mokkink, L. B., Terwee, C. B., & Chinapaw, M. J. M. (2017). Systematic review of childhood sedentary behavior questionnaires: What do we know and what is next? *Sports Medicine, 47*(4), 677-699. doi:10.1007/s40279-016-0610-1

High, P. C. (2008). School Readiness. *Pediatrics, 121*(4), e1008-e1015. doi:10.1542/peds.2008-0079

Hinkley, T., O'connell, E., Okely, A. D., Crawford, D., Hesketh, K., & Salmon, J. (2012). Assessing volume of accelerometry data for reliability in preschool children. *Medicine & Science in Sports & Exercise, 44*(12), 2436-2441. doi:10.1249/MSS.0b013e3182661478

Hinkley, T., Timperio, A., Watson, A., Duckham, R. L., Okely, A. D., Cliff, D., . . . Hesketh, K. D. (2020). Prospective associations with physiological, psychosocial and educational outcomes of meeting Australian 24-Hour Movement Guidelines for the Early Years. *International Journal of Behavioral Nutrition and Physical Activity, 17*(1), 36. doi:10.1186/s12966-020-00935-6

Hislop, J., Law, J., Rush, R., Grainger, A., Bulley, C., Reilly, J. J., & Mercer, T. (2014). An investigation into the minimum accelerometry wear time for reliable estimates of habitual physical activity and definition of a standard measurement day in pre-school children. *Physiological Measurement, 35*(11), 2213.

Hjorth, M. F., Chaput, J.-P., Damsgaard, C. T., Dalskov, S.-M., Michaelsen, K. F., Tetens, I., & SjÖDin, A. (2012). Measure of sleep and physical activity by a single accelerometer: Can a waist-worn ActiGraph adequately measure sleep in children? *Sleep and Biological Rhythms, 10*(4), 328-335. doi:10.1111/j.1479-8425.2012.00578.x

Horst, K., Paw, M. J. C., Twisk, J. W. R., & Mechelen, W. (2007). A brief review on correlates of physical activity and sedentariness in youth. *Medicine & Science in Sports & Exercise, 39*(8), 1241-1250.

Howard, S. J., & Melhuish, E. (2017). An early years toolbox for assessing early executive function, language, self-regulation, and social development: Validity, reliability, and preliminary norms. *Journal of Psychoeducational Assessment, 35*(3), 255-275.

Howard, S. J., & Okely, A. D. (2015). Catching fish and avoiding sharks. *Journal of Psychoeducational Assessment, 33*(6), 585-596. doi:doi:10.1177/0734282914562933

Huang, X.-N., Wang, H.-S., Chang, J.-J., Wang, L.-H., Liu, X.-C., Jiang, J.-X., & An, L. (2016). Feeding methods, sleep arrangement, and infant sleep patterns: A chinese population-based study. *World Journal of Pediatrics, 12*(1), 66-75.

Hughes, A. R., Muggeridge, D. J., Gibson, A.-M., Johnstone, A., & Kirk, A. (2016). Objectively measured sedentary time in children and their parents. *Aims Public Health, 3*(4), 823-836.

Hysing, M., Harvey, A. G., Torgersen, L., Ystrom, E., Reichborn-Kjennerud, T., & Sivertsen, B. (2014). Trajectories and predictors of nocturnal awakenings and sleep duration in infants. *Journal of Developmental & Behavioral Pediatrics, 35*(5), 309-316.

Janssen, X., Cliff, D. P., Reilly, J. J., Hinkley, T., Jones, R. A., Batterham, M., . . . Okely, A. D. (2013). Predictive validity and classification accuracy of ActiGraph energy expenditure equations and cut-points in young children. *PLOS ONE, 8*(11), e79124. doi:10.1371/journal.pone.0079124

Johansson, E., Ekelund, U., Nero, H., Marcus, C., & Hagströmer, M. (2015). Calibration and cross-validation of a wrist-worn ActiGraph in young preschoolers. *Pediatric Obesity, 10*(1), 1-6. doi:10.1111/j.2047-6310.2013.00213.x

Johansson, E., Larisch, L. M., Marcus, C., & Hagstromer, M. (2016). Calibration and validation of a wrist- and hip-worn ActiGraph accelerometer in 4-year-old children. *PLOS ONE, 11*(9), e0162436. doi:https://dx.doi.org/10.1371/journal.pone.0162436

John, D., Miller, R., Kozey-Keadle, S., Caldwell, G., & Freedson, P. (2012). Biomechanical examination of the 'plateau phenomenon'in ActiGraph vertical activity counts. *Physiological Measurement, 33*(2), 219.

Jones, D. E., Greenberg, M., & Crowley, M. (2015). Early Social-Emotional Functioning and Public Health: The Relationship Between Kindergarten Social Competence and Future Wellness. *Am J Public Health, 105*(11), 2283-2290. doi:10.2105/ajph.2015.302630

Kinder, J. R., Lee, K. A., Thompson, H., Hicks, K., Topp, K., & Madsen, K. A. (2012). Validation of a hip-worn accelerometer in measuring sleep time in children. *Journal of Pediatric Nursing, 27*(2), 127-133. doi:http://dx.doi.org/10.1016/j.pedn.2010.11.004

Klesges, R. C., Coates, T. J., Moldenhauer-Klesges, L. M., Holzer, B., Gustavson, J., & Barnes, J. (1984). The FATS: An observational system for assessing physical activity in children and associated parent behavior. *Behavioral Assessment, 6*(4), 333-345.

Kushida, C. A., Littner, M. R., Morgenthaler, T., Alessi, C. A., Bailey, D., Coleman, J., Jr., . . . Wise, M. (2005). Practice Parameters for the Indications for Polysomnography and Related Procedures: An Update for 2005. *Sleep, 28*(4), 499-523. doi:10.1093/sleep/28.4.499

Kuzik, N., & Carson, V. (2018). Accelerometer Bluetooth proximity validation in parents and early years children. *Measurement in Physical Education and Exercise Science, 22*(4), 287-293. doi:10.1080/1091367X.2018.1442335

Kuzik, N., Poitras, V. J., Tremblay, M. S., Lee, E.-Y., Hunter, S., & Carson, V. (2017). Systematic review of the relationships between combinations of movement behaviours and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 849.

Lemoigne, Y. (2008). Molecular imaging computer reconstruction and practice. In A. Caner (Ed.). Dordrecht ;: Springer Science + Business Media B.V.

Leppänen, M. H., Ray, C., Wennman, H., Alexandrou, C., Sääksjärvi, K., Koivusilta, L., . . . Roos, E. (2019). Compliance with the 24-h movement guidelines and the relationship with anthropometry in Finnish preschoolers: the DAGIS study. *BMC Public Health, 19*(1), 1618. doi:10.1186/s12889-019-7967-7

Lubans, D. R., Morgan, P. J., Cliff, D. P., Barnett, L. M., & Okely, A. D. (2010). Fundamental movement skills in children and adolescents. *Sports Medicine, 40*(12), 1019-1035.

Luo, Z. C., Albertsson-Wikland, K., & Karlberg, J. (1998a). Target height as predicted by parental heights in a population-based study. *Pediatr Res, 44*(4), 563-571. doi:10.1203/00006450-199810000-00016

Mâsse, L. C., & Watts, A. W. (2013). Stimulating innovations in the measurement of parenting constructs. *Childhood Obesity, 9*(Suppl 1), S-5-S-13. doi:10.1089/chi.2013.0041

McAlister, D. (1879). The law of the geometric mean. *Proceedings of the royal society of london, 29*(196-199), 367-376.

Meltzer, L. J., Montgomery-Downs, H. E., Insana, S. P., & Walsh, C. M. (2012). Use of actigraphy for assessment in pediatric sleep research. *Sleep Medicine Reviews, 16*(5), 463-475. doi:10.1016/j.smrv.2011.10.002

Mendonça, G., Cheng, L. A., Mélo, E. N., & Farias Júnior, J. C. (2014). Physical activity and social support in adolescents: A systematic review. *Health Education Research, 29*.

Meredith-Jones, K., Williams, S., Galland, B., Kennedy, G., & Taylor, R. (2016). 24 h accelerometry: Impact of sleep-screening methods on estimates of sedentary behaviour and physical activity while awake. *Journal of Sports Sciences, 34*(7), 679-685. doi:https://dx.doi.org/10.1080/02640414.2015.1068438

Migueles, J. H., Cadenas-Sanchez, C., Ekelund, U., Delisle Nyström, C., Mora-Gonzalez, J., Löf, M., . . . Ortega, F. B. (2017). Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations. *Sports Medicine, 47*(9), 1821-1845. doi:10.1007/s40279-017-0716-0

Mileva-Seitz, V. R., Bakermans-Kranenburg, M. J., Battaini, C., & Luijk, M. P. C. M. (2017). Parent-child bed-sharing: The good, the bad, and the burden of evidence. *Sleep Medicine Reviews, 32*, 4-27. doi:http://dx.doi.org/10.1016/j.smrv.2016.03.003

Mindell, J. A., Sadeh, A., Kwon, R., & Goh, D. Y. (2013). Cross-cultural differences in the sleep of preschool children. *Sleep Medicine, 14*(12), 1283-1289. doi:10.1016/j.sleep.2013.09.002

Mindell, J. A., Sadeh, A., Wiegand, B., How, T. H., & Goh, D. Y. (2010). Cross-cultural differences in infant and toddler sleep. *Sleep Medicine, 11*(3), 274-280. doi:10.1016/j.sleep.2009.04.012

Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., . . . Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences, 108*(7), 2693-2698. doi:10.1073/pnas.1010076108

Morgan, P. L., Farkas, G., Hillemeier, M. M., Hammer, C. S., & Maczuga, S. (2015). 24-month-old children with larger oral vocabularies display greater academic and behavioral functioning at kindergarten entry. *Child Development, 86*(5), 1351-1370. doi:10.1111/cdev.12398

Must, A., & Strauss, R. S. (1999). Risks and consequences of childhood and adolescent obesity. *International Journal of Obesity, 23*(2), S2-S11. doi:10.1038/sj.ijo.0800852

Oftedal, S., Bell, K. L., Davies, P. S., Ware, R. S., & Boyd, R. N. (2014). Validation of accelerometer cut points in toddlers with and without cerebral palsy. *Medicine & Science in Sports & Exercise, 46*(9), 1808-1815. doi:https://dx.doi.org/10.1249/MSS.0000000000000299

Østbye, T., Malhotra, R., Stroo, M., Lovelady, C., Brouwer, R., Zucker, N., & Fuemmeler, B. (2013). The effect of the home environment on physical activity and dietary intake in preschool children. *International Journal of Obesity, 37*(10), 1314-1321. doi:http://dx.doi.org/10.1038/ijo.2013.76

Owen, N., Sugiyama, T., Eakin, E., Gardiner, P., Tremblay, M., & Sallis, J. (2011). Adults' sedentary behavior: Determinants and interventions. *American Journal of Preventive Medicine, 41*(2), 189-196.

Pate, R. R., Almeida, M. J., McIver, K. L., Pfeiffer, K. A., & Dowda, M. (2006). Validation and calibration of an accelerometer in preschool children. *Obesity, 14*(11), 2000-2006. doi:https://dx.doi.org/10.1038/oby.2006.234

Pawlowsky-Glahn, V., Egozcue, J. J., & Tolosana-Delgado, R. (2015). *Modeling and analysis of compositional data*: John Wiley & Sons.

Pearson, K. (1897). Mathematical contributions to the theory of evolution.—on a form of spurious correlation which may arise when indices are used in the measurement of organs. *Proceedings of the royal society of london, 60*(359-367), 489-498.

Pedišić, Ž. (2014). Measurement issues and poor adjustments for physical activity and sleep undermine sedentary behaviour research - the focus should shift to the balance between sleep, sedentary behaviour, standing and activity. *Kinesiology: International journal of fundamental and applied kinesiology, 46*(1), 135-146.

Pedišić, Ž., Dumuid, D., & Olds, T. (2017). Integrating sleep, sedentary behaviour, and physical activity research in the emerging field of time-use epidemiology: Definitions, concepts, statistical methods, theoretical framework, and future directions. *Kinesiology: International journal of fundamental and applied kinesiology, 49*(2), 10-11.

Piek, J. P., Dawson, L., Smith, L. M., & Gasson, N. (2008). The role of early fine and gross motor development on later motor and cognitive ability. *Human Movement Science, 27*(5), 668-681. doi:https://doi.org/10.1016/j.humov.2007.11.002

Poitras, V. J., Gray, C. E., Borghese, M. M., Carson, V., Chaput, J.-P., Janssen, I., . . . Kho, M. E. (2016). Systematic review of the relationships between objectively measured physical activity and health indicators in school-aged children and youth 1. *Applied Physiology, Nutrition, and Metabolism, 41*(6), S197-S239.

Poitras, V. J., Gray, C. E., Janssen, X., Aubert, S., Carson, V., Faulkner, G., . . . Tremblay, M. (2017). Systematic review of the relationships between sedentary behavior and health indicators in the early years (aged 0-4 years). *BMC Public Health, 17*(5), 868.

Pugliese, J., & Tinsley, B. (2007). Parental socialization of child and adolescent physical activity: A meta-analysis. *Journal of Family Psychology, 21*.

Puhl, J., Greaves, K., Hoyt, M., & Baranowski, T. (1990). Children's activity rating scale (cars): Description and calibration. *Research Quarterly for Exercise and Sport, 61*(1), 26-36. doi:10.1080/02701367.1990.10607475

Pulakka, A., Cheung, Y. B., Ashorn, U., Penpraze, V., Maleta, K., Phuka, J. C., & Ashorn, P. (2013). Feasibility and validity of the ActiGraph GT3X accelerometer in measuring physical activity of Malawian toddlers. *Acta Paediatrica, 102*(12), 1192-1198. doi:https://dx.doi.org/10.1111/apa.12412

Quante, M., Kaplan, E. R., Rueschman, M., Cailler, M., Buxton, O. M., & Redline, S. (2015). Practical considerations in using accelerometers to assess physical activity, sedentary behavior, and sleep. *Sleep Health: Journal of the National Sleep Foundation, 1*(4), 275-284. doi:10.1016/j.sleh.2015.09.002

Rhodes, R. E., & Quinlan, A. (2014). *The family as a context for physical activity promotion* (2 ed.). New York: Routledge.
Robinson, L. E., Stodden, D. F., Barnett, L. M., Lopes, V. P., Logan, S. W., Rodrigues, L. P., & D'Hondt, E. (2015). Motor Competence and its Effect on Positive Developmental Trajectories of Health. *Sports Medicine, 45*(9), 1273-1284. doi:10.1007/s40279-015-0351-6
Rosenberger, M. E., Buman, M. P., Haskell, W. L., McConnell, M. V., & Carstensen, L. L. (2016). 24 hours of sleep, sedentary behavior, and physical activity with nine wearable devices. *Medicine & Science in Sports & Exercise, 48*(3), 457-465. doi:10.1249/MSS.0000000000000778
Ruiz, R., Gesell, S. B., Buchowski, M. S., Lambert, W., & Barkin, S. L. (2011). The relationship between hispanic parents and their preschool-aged children's physical activity. *Pediatrics, 127*(5), 888-895. doi:10.1542/peds.2010-1712
Saarni, C. (1999). *The development of emotional competence*: Guilford Press.
Sadeh, A. (2004). A brief screening questionnaire for infant sleep problems: Validation and findings for an internet sample. *Pediatrics, 113*(6), e570-e577. doi:10.1542/peds.113.6.e570
Sadeh, A. (2015). III. Sleep assessment methods. *Monographs of the Society for Research in Child Development, 80*(1), 33-48. doi:10.1111/mono.12143
Sadeh, A., Acebo, C., Seifer, R., Aytur, S., & Carskadon, M. A. (1995). Activity-based assessment of sleep-wake patterns during the 1st year of life. *Infant Behavior and Development, 18*(3), 329-337.
Sadeh, A., Alster, J., Urbach, D., & Lavie, P. (1989). Actigraphically based automatic bedtime sleep-wake scoring: validity and clinical applications. *Journal of ambulatory monitoring, 2*(3), 209-216.
Sallis, J. F., Owen, N., & Fisher, E. (2015). *Ecological models of health behavior* (5 ed.). San Francisco: Jossey-Bass.
Sallis, J. F., Owen, N., & Fotheringham, M. J. (2000). Behavioral epidemiology: a systematic framework to classify phases of research on health promotion and disease prevention. *Annals of Behavioral Medicine, 22*(4), 294-298.
Sallis, J. F., Prochaska, J. J., & Taylor, W. C. (2000). A review of correlates of physical activity of children and adolescents. *Medicine & Science in Sports & Exercise, 32*.
Salmon, J., Tremblay, M., Marshall, S., & Hume, C. (2011). Health risks, correlates, and interventions to reduce sedentary behavior in young people. *American Journal of Preventive Medicine, 41*(2), 197-206. doi:http://dx.doi.org/10.1016/j.amepre.2011.05.001
Sameroff, A. (1975). Transactional models in early social relations. *Human Development, 18*(1-2), 65-79.
Schmutz, E. A., Leeger-Aschmann, C. S., Radtke, T., Muff, S., Kakebeeke, T. H., Zysset, A. E., . . . Meyer, A. H. (2017). Correlates of preschool children's objectively measured physical activity and sedentary behavior: A cross-sectional analysis of the splashy study. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 1.
Scholle, S., Scholle, H. C., Kemper, A., Glaser, S., Rieger, B., Kemper, G., & Zwacka, G. (2003). First night effect in children and adolescents undergoing polysomnography for sleep-disordered breathing. *Clinical Neurophysiology, 114*(11), 2138-2145. doi:https://doi.org/10.1016/S1388-2457(03)00209-8

Seale, J., & Rumpler, W. (1997). Comparison of energy expenditure measurements by diet records, energy intake balance, doubly labeled water and room calorimetry. *European Journal of Clinical Nutrition, 51*(12), 856-863.
Secker, D. (2010). Promoting optimal monitoring of child growth in Canada: using the new WHO growth charts. *Can J Diet Pract Res, 71*(1), e1-3. doi:10.3148/71.1.2010.54
Shaul, S., & Schwartz, M. (2014). The role of the executive functions in school readiness among preschool-age children. *Reading and Writing, 27*(4), 749-768. doi:10.1007/s11145-013-9470-3
Sirard, J. R., & Pate, R. R. (2001). Physical activity assessment in children and adolescents. *Sports Medicine, 31*(6), 439-454. doi:10.2165/00007256-200131060-00004
Sirard, J. R., Trost, S. G., Pfeiffer, K. A., Dowda, M., & Pate, R. R. (2005). Calibration and evaluation of an objective measure of physical activity in preschool children. *Journal of Physical Activity and Health, 2*(3), 345-357.
Sluijs, E. M. F., Kriemler, S., & McMinn, A. M. (2011). The effect of community and family interventions on young people's physical activity levels: A review of reviews and updated systematic review. *British Journal of Sports Medicine, 45*.
Sluijs, E. M. F., McMinn, A. M., & Griffin, S. J. (2007). Effectiveness of interventions to promote physical activity in children and adolescents: Systematic review of controlled trials. *Bmj, 335*.
Smith, C., Galland, B., Taylor, R., & Meredith-Jones, K. (2020). ActiGraph GT3X+ and Actical Wrist and Hip Worn Accelerometers for Sleep and Wake Indices in Young Children Using an Automated Algorithm: Validation With Polysomnography. *Frontiers in Psychiatry, 10*, 958-958. doi:10.3389/fpsyt.2019.00958
Spence, J. C., & Lee, R. E. (2003). Toward a comprehensive model of physical activity. *Psychology of Sport and Exercise, 4*(1), 7-24. doi:http://dx.doi.org/10.1016/S1469-0292(02)00014-6
Sterdt, E., Liersch, S., & Walter, U. (2013). Correlates of physical activity of children and adolescents: A systematic review of reviews. *Health Education Journal, 73*.
Tandon, P. S., Saelens, B. E., Zhou, C., Kerr, J., & Christakis, D. A. (2013). Indoor versus outdoor time in preschoolers at child care. *American Journal of Preventive Medicine, 44*(1), 85-88. doi:https://doi.org/10.1016/j.amepre.2012.09.052
Taylor, R. W., Haszard, J. J., Meredith-Jones, K. A., Galland, B. C., Heath, A.-L. M., Lawrence, J., . . . Taylor, B. J. (2018). 24-h movement behaviors from infancy to preschool: cross-sectional and longitudinal relationships with body composition and bone health. *International Journal of Behavioral Nutrition and Physical Activity, 15*(1), 118.
Taylor, W. C., Baranowski, T., & Sallis, J. F. (1994). Family determinants of childhood physical activity: A social-cognitive model. In R. K. Dishman (Ed.), *Advances in Exercise Adherence* (pp. 319–342). Champaign, IL: Human Kinetics.
Thoman, E. B. (1990). Sleeping and waking states in infants: A functional perspective. *Neuroscience & Biobehavioral Reviews, 14*(1), 93-107.
Thoman, E. B. (2006). Co-sleeping, an ancient practice: Issues of the past and present, and possibilities for the future. *Sleep Medicine Reviews, 10*(6), 407-417. doi:https://doi.org/10.1016/j.smrv.2005.12.001
Touchette, E., Côté, S., Petit, D., Liu, X., Boivin, M., Falissard, B., . . . Montplaisir, J. (2009). Short nighttime sleep-duration and hyperactivity trajectories in early childhood. *Pediatrics, 124*(5), e985-e993.

Tremblay, M. S. (2019). Introducing 24-Hour Movement Guidelines for the Early Years: A New Paradigm Gaining Momentum. *Journal of Physical Activity and Health, 1*(aop), 1-4.
Tremblay, M. S., Chaput, J.-P., Adamo, K. B., Aubert, S., Barnes, J. D., Choquette, L., . . . Carson, V. (2017b). Canadian 24-hour movement guidelines for the early years (0-4 years): An integration of physical activity, sedentary behaviour, and sleep. *BMC Public Health, 17*(5), 874.
Trost, S. G. (2007). State of the art reviews: Measurement of physical activity in children and adolescents. *American Journal of Lifestyle Medicine, 1*(4), 299-314.
Trost, S. G., Fees, B. S., Haar, S. J., Murray, A. D., & Crowe, L. K. (2012). Identification and validity of accelerometer cut-points for toddlers. *Obesity, 20*(11), 2317-2319. doi:10.1038/oby.2011.364
Trost, S. G., & Loprinzi, P. D. (2011). Parental influences on physical activity behavior in children and adolescents: A brief review. *American Journal of Lifestyle Medicine, 5*.
Tudor-Locke, C., Barreira, T., Schuna, J., Mire, E., Chaput, J., Fogelholm, M., . . . Katzmarzyk, P. (2015). Improving wear time compliance with a 24-hour waist-worn accelerometer protocol in the international study of childhood obesity, lifestyle and the environment (iscole). *International Journal of Behavioral Nutrition and Physical Activity, 12*(1), 11. doi:10.1186/s12966-015-0172-x
Tudor-Locke, C., Barreira, T. V., Schuna, J. M., Jr., Mire, E. F., & Katzmarzyk, P. T. (2014). Fully automated waist-worn accelerometer algorithm for detecting children's sleep-period time separate from 24-h physical activity or sedentary behaviors. *Applied Physiology, Nutrition, and Metabolism, 39*(1), 53-57. doi:10.1139/apnm-2013-0173
Vale, S., Santos, R., Silva, P., Soares-Miranda, L., & Mota, J. (2009). Preschool children physical activity measurement: Importance of epoch length choice. *Pediatric Exercise Science, 21*(4), 413-420.
Van Cauwenberghe, E., Gubbels, J., De Bourdeaudhuij, I., & Cardon, G. (2011a). Feasibility and validity of accelerometer measurements to assess physical activity in toddlers. *International Journal of Behavioral Nutrition and Physical Activity, 8*(1), 67. doi:10.1186/1479-5868-8-67
Van Cauwenberghe, E., Labarque, V., Trost, S. G., Bourdeaudhuij, I., & Cardon, G. (2011b). Calibration and comparison of accelerometer cut points in preschool children. *Pediatric Obesity, 6*(2Part2).
Van den Boogaart, K. G., & Tolosana-Delgado, R. (2013). *Analyzing compositional data with R* (Vol. 122): Springer.
Vaughn, A., Hales, D., & Ward, D. S. (2013). Measuring the physical activity practices used by parents of preschool children. *Medicine & Science in Sports & Exercise, 45*(12), 2369.
Webber, K. J., & Loescher, L. J. (2013). A systematic review of parent role modeling of healthy eating and physical activity for their young african-american children. *Journal for Specialists in Pediatric Nursing, 18*.
Welk, G. J. (2002). *Physical activity assessments for health-related research*: Human Kinetics.
Welk, G. J., Wood, K., & Morss, G. (2003). Parental influences on physical activity in children: An exploration of potential mechanisms. *Pediatric Exercise Science, 15*(1), 19-33.
Wiebe, S. A., & Karbach, J. (2018). *Executive function : development across the life span*: New York : Routledge, Taylor & Francis Group, 2018.
World Health Organization. (1948). *Constitution of the world health organization.* Geneva.

Yao, C. A., & Rhodes, R. E. (2015). Parental correlates in child and adolescent physical activity: A meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity, 12*(1), 1-38. doi:10.1186/s12966-015-0163-y

Zelazo, P. D., Anderson, J. E., Richler, J., Wallner-Allen, K., Beaumont, J. L., & Weintraub, S. (2013). II. NIH toolbox cognition battery (CB): Measuring executive function and attention. *Monographs of the Society for Research in Child Development, 78*(4), 16-33. doi:10.1111/mono.12032

3 Manuscript 1

Machine Learning Sleep Classification in Preschoolers using Waist-Worn ActiGraphs

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3.1 Abstract

Purpose: Accurately classifying movement behaviours (i.e., sleep, sedentary behaviour, physical activity) in preschool-aged children is essential for understanding 24-hour movement behaviours; however automated techniques to categorize sleep are lacking. The purpose of this study was to create a sleep classification technique for waist-worn ActiGraph accelerometers in preschool-aged children.

Methods: Children recruited in Edmonton, Canada were instructed to wear ActiGraph WGT3X-BT accelerometers on their right hip for 7 days (24 hours/day). Ground truth *nap*, *sleep*, and *wake* were estimated through visual inspection of accelerometer data, guided by sleep log-sheets and previously published visual inspection heuristics. Raw accelerometer data (30Hz) were used to generate 144 features aggregated to 1-minute epochs. Machine learning classification (i.e., Random Forest and Hidden Markov Modeling) predicted *nap*, *sleep*, and *wake*. A simplified prediction formula was also created using features (n=10) with the highest mean decrease in Gini index during training of Random Forests, and temporally smoothed with rolling median calculations.

Results: Children (n=89, mean age=4.5 years, 67% boys) contributed 1,091,232,000 raw accelerometer observations. Overall classification accuracy of the Random Forest and Hidden Markov Modeling classifier was 96.2% (95% CI: 96.1, 96.2%), with a Kappa score of 0.93. Additionally, overall classification accuracy for the temporally smoothed simplified formula was 93.7% (95%CI: 93.6, 93.7%) with Kappa=0.87. *Nap* prediction accuracy was 99.8% for the final machine learning model, and 86.1% for the simplified formula. For participant-level daily summaries, significant differences were found between machine learning and ground truth

behaviour predictions, whereas non-significant differences were found between the simplified formulas and ground truth predictions.

Conclusion: Predictions for both machine learning and the simplified formula had almost perfect agreement with visual inspection ground truth measurements.

3.2 Introduction

Movement behaviours patterns in isolation (i.e., adequate sleep, less sedentary behaviour, and more physical activity) have demonstrated numerous health benefits to aspects of physical, cognitive, and social-emotional development in preschool-aged children (3-5 years) (Carson et al., 2017b; Chaput et al., 2017b; Poitras et al., 2017). While combinations of movement behaviours have demonstrated health benefits for physical development, overall the body of evidence for combinations of movement behaviours is lacking (Carson, Tremblay, & Chastin, 2017f; Kuzik et al., 2017; Taylor et al., 2018). Movement behaviours could holistically be important for overall optimal development in preschool-aged children but ultimately the lack of research in this area prevents any firm conclusions.

Measurement challenges could be one reason for the lack of research on combinations of movement behaviours in preschool-aged children. In fact, refining measurement techniques has been identified as a key area for future research in time use epidemiology in all age groups (Pedišić et al., 2017). Accelerometers are the preferred tool for measuring movement behaviours in field settings, based on the potential for adequate feasibility, reliability, and validity (Sadeh et al., 1995; Van Cauwenberghe et al., 2011a). However, accelerometer-related methodological decisions (e.g., device selection, classification technique) can influence the quantification of movement behaviours (Cliff et al., 2009; Migueles et al., 2017). ActiGraph is the most widely used accelerometer for movement behaviour research (Cliff et al., 2009; Migueles et al., 2017). Though numerous studies have created physical activity and sedentary behaviour classification techniques for preschool-aged children using the ActiGraph, no studies have created a sleep classification technique (Migueles et al., 2017). This could be due to the added complication of classifying daytime sleep (i.e., naps) in preschool-aged children (Galland, Meredith-Jones, Terrill, & Taylor, 2014b). Thus, 24-hour movement behaviour studies tend to rely on visual inspection of accelerometer data by researchers, parental–report estimates of sleep time, or a combination of these methods to measure sleep duration (Carson et al., 2017f; Zhang et al., 2019).

To reduce researcher and participant burden, an automated technique for classifying sleep in preschool-aged children is needed. Willets et al. (Willetts, Hollowell, Aslett, Holmes, & Doherty, 2018) recently extracted features from raw accelerometer data and applied machine learning techniques to successfully classify sleep in adults with 97% accuracy using the Axivity AX3 accelerometer. The application of similar techniques could be promising for improving 24-hour movement behaviour classification in preschool-aged children. Therefore, the purpose of this study was to create a sleep classification technique for waist-worn ActiGraph accelerometers in preschool-aged children using a feature extraction and machine learning process.

3.3 Methods

3.3.1 Participants

Participants were children aged 3-5 years, whose primary language at home was English, from the Parent-Child Movement Behaviours and Pre-School Children's Development study. Parents/guardians of children were recruited from Edmonton, Canada and surrounding areas through a local division of Sportball, a program that aims to teach children fundamental sport skills through play. Parents were approached in person by the lead investigator during Sportball summer camps and at Sportball classes. A total of 60/102 children were recruited from summer camps, but participation rates and reasons for non-participation from classes were not tracked due to logistical constraints. Additionally, the local Sportball organization distributed recruitment materials to parents via email and social media. It is unknown how many eligible parents received the email or viewed the social media posts, or their reasons for non-participation. In total, 131 parents/guardians agreed to participate. Ethical approval was obtained from the University of Alberta Research Ethics Board. Parents/guardians provided written informed consent.

3.3.2 <u>Procedures</u>

From July to November 2018, children were provided accelerometers, and parents received verbal and written study protocol instructions, a log-sheet to track sleep and accelerometer wear time, as well as a demographic questionnaire. Children were given ActiGraph WGT3X-BT accelerometers (dynamic range: ±8g) programmed at 30 Hz, to wear in free living conditions. Parents were instructed to have children wear the accelerometer on an elastic belt on their right hip for 24 hours a day over 7 days, except during water-based activities. After being given to families, accelerometers were programmed to begin recording at the next instance of 00:00:00. After the accelerometer wear period, the lead investigator visited the homes of parents or an alternative preferred location (n=2) to collect the study materials. Accelerometer data were downloaded as both raw and 15-second epoch low-frequency extension files.

3.3.3 <u>Behaviour Prediction</u>

The process of predicting behaviours (i.e., "*nap*" [i.e., daytime sleep], "*sleep*" [i.e., nighttime sleep], and "*wake*") for this study was conducted in three phases: a ground truth measure was estimated, data was processed to generate features, and features were used in analyses to predict behaviours. Ground truth measures are observations intended to best represent the actual behaviour of interest that prediction analyses ideally achieve perfect agreement with. Since the accelerometers used in this study measured movement in three axes, data was categorized into features representing time (e.g., mean value in 1 minute), frequency (e.g., fast Fourier transformations), or angular (e.g., angle of accelerometer relative a particular axis) domains. Further, non-accelerometer features (e.g., age of participant) were used to improve predictive models. Subsequently, these features were used to build models to predict behaviours by first training models with a subset of the total data (training data), then evaluating the models predictive capacity on the remainder of the total data (testing data). Within this study, the predictive models were Random Forests, Hidden Markov Modeling (HMM), and simplified logistic regression formulas.

3.3.3.1 Ground Truth Measurement

All data management and analyses were conducted in R (version 3.6.1, *"Action of the Toes"*). Visual inspection sleep classification was considered the ground truth. Accelerometer 15-second epoch files were used to classify data into the categories of *nap*, *sleep*, or *wake* using visual inspection. Since the main purpose of this study was sleep classification, non-wear time was considered *wake*. Visual inspection was guided by the log-sheets and heuristics according to previous visual inspection literature (Tudor-Locke et al., 2014). Specifically, figures were created for each day of data that plotted the x-axis of accelerometer data against time. Each plot also included highlighting to indicate log-sheet sleep times, as well as rules implemented to guide visual inspection based on inclinometer values, steps, and vector magnitude (Tudor-Locke et al., 2014). Figures were only created if log-sheet data were available for the morning *wake* and night *sleep* indicators, thus all included days in the analysis consisted of a full 24-hours. Visual inspection classification decisions were made at 1-minute intervals.

3.3.3.2 Raw Accelerometer Data Processing

Raw accelerometer data were first calibrated using the GGIR g.calibrate function in R. Then calibrated raw data were aggregated into non-overlapping 60-second windows, or 60-second intervals, to align with the granularity of ground truth, and features were calculated for each window using the R packages GGIR (n=18 features) (Migueles, Rowlands, Huber, Sabia, & van Hees, 2019) and TLBC (n=38 features) (Ellis, Kerr, Godbole, Staudenmayer, & Lanckriet, 2016). Modifications were made to the TLBC package to calculate additional features (n=85 features) (ActiGraph Corp, 2017; Vaha-Ypya, Vasankari, Husu, Suni, & Sievanen, 2015; Willetts et al., 2018; Zhang, Rowlands, Murray, & Hurst, 2012). Calculated features were based on previous raw accelerometer classification literature (ActiGraph Corp, 2017; Ellis et al., 2016; Mannini, Intille, Rosenberger, Sabatini, & Haskell, 2013; Migueles et al., 2019; Vaha-Ypya et al., 2015; Willetts et al., 2018; Zhang et al., 2012). When possible, features were extracted for the x-, y-, and z-axes independently, then a mean and vector magnitude summary of the axes were calculated. In total, 141 features were calculated, as well the child's age, sex, and their lux values were added to the features, making a total of 144 features for each 1-minute observation. For a full list of features and their source, see Supplemental Digital Content 2.

3.3.3.3 Machine Learning Predictions

A Random Forest classifier was used to predict *nap*, *sleep*, or *wake* states or behaviours, using the 144 accelerometer features. Random Forests are ensemble learning—a process of creating and combining multiple models—using a collection of randomized decision trees (Breiman, 2001). During the training phase in this study, each decision tree was trained with a random subset of extracted features equal to the square root of the total number of features (sampled without replacement) and a random subset of ground truth training examples equal to the total number of 1-minute observations or rows in the training set (sampled with replacement). Decision trees consist of terminal leaves indicating predicted behaviours (e.g., *sleep*) that are reached through a series of splitting nodes representing an accelerometer feature distinguishing between behaviours. Beginning at the first node, features are iteratively used to sort the ground truth training examples for that decision tree into their terminal leaves. To estimate the importance of each feature, the Gini index can be calculated at each node, which is a marker of how well a feature splits observations into their correct behaviours at a node (Breiman, 2001). Once the model is trained, predictions can be made on test data by applying each decision tree to test data and following that trees previous decision process for classification. Each individual decision tree sorts the testing data into predicted behaviours, and when considered with all the trees is said to cast a vote for the predicted behaviour for that observation. For instance, decision trees can be aggregated into a forest by taking the median behaviour classification, or vote, for each observation in the test data. For the current study, models were set to use 500 decision trees for each Random Forest model.

Additionally, to compensate for the unbalanced proportion of different behaviours (i.e., *nap* behaviour makes up a small proportion compared to *sleep* or *wake*), balanced Random Forests with down sampling were used during the training phase (Chen, 2004). Specifically, down sampling indicates that training data for each tree was randomly sampled (with replacement) and each behaviour had the same number of observations as the behaviour with the lowest number of observations. For instance, if the total observations for each behaviour were *nap*=10, *sleep*=100, and *wake*=200, then training data for each tree would randomly sample 10 observations for each behaviour.

One drawback of Random Forest classification models is the lack of temporal predictions, thus HMM can be used to examine the temporal sequencing of data (Zucchini, MacDonald, & Langrock, 2017). Within this study, the HMM used three parameters to model probabilities of transitioning between behaviours: ground truth probability, transition probability, and emission probability. The ground truth probability is the prior probability of randomly observing each behaviour. For instance, if an individual has 10 hours or 600 minutes of *sleep* per 24 hours or 1440 minutes, the ground truth probability of *sleep* would be 600/1440. The transition probability is the probability of moving from one behaviour to another. For instance, it is more likely that an individual would transition from *sleep* to another epoch of *sleep* (i.e., 600/1440), instead of *sleep* to an epoch of *wake*, since the latter transition typically only happens once per day (i.e., 1/1440). Lastly, the emission probabilities are summed Random Forest behaviour prediction probabilities for each ground truth observation. Specifically, a confusion matrix is calculated based on the vote probabilities in the Random Forest for each ground truth behaviour. Using these three parameters of the HMM, the Viterbi algorithm was applied to the results of the Random Forest to determine the most likely temporal sequence of behaviours (Forney, 1973). For instance, if a sequence of predicted behaviours included a *wake* epoch with several hours of *sleep* epochs on either side, the Viterbi algorithm could use the parameters of the HMM and smooth this predicted behaviour to a *sleep* epoch.

3.3.3.4 Simplified Formula Predictions

To improve the feasibility of reproducing the results from this study, a simplified formula was created to apply to accelerometer data. Variable or feature importance metrics were calculated during Random Forest creation. The ten features or variables with the highest mean decrease of Gini index were selected. When a feature sorts the observations at a node, the Gini index will decrease in each branch as the observations become more homogenous, until the branch contains only one behaviour (Gini index = 0.0). Thus, the mean decrease in Gini index from the feature to the new branches represents the features ability to sort observations into their correct behaviours. These 10 variables were used as predictors in a logistic regression model with the outcome of *sleep* status (*sleep* = 1 [i.e., *nap* and *sleep*] and *wake* = 0). *Nap* and *sleep* behaviours were combined to simplify the model, but predictions of *sleep* occurring during ground truth *nap* behaviours were later reclassified as *nap* to determine the accuracy of *nap* predictions. The regression coefficients and intercept from this model were used to create a formula to estimate the probability of being in a *sleep* (i.e., *nap* and *sleep*) behaviour in each epoch. To dichotomize the predictions, a threshold for probability was calculated using the highest average between sensitivity and specificity in a Receiver Operating Characteristic (ROC) curve analysis. To determine what size of window to use to smooth predictions, rolling medians were calculated with overlapping window sizes ranging from 3 minutes to 201 minutes. For example, the value of time=10 with an overlapping window size of 3 minutes would be the median from times 9-11, likewise when the window moved to time=11 the value would be the median from times 10-12. Informal testing was conducted on multiple models and window sizes, with most showing ~45 minutes was an optimal window, so 201 was arbitrarily chosen as a maximum and 3 was chosen as the lowest possible odd window size for formal testing. Accuracy was calculated for each behaviour (i.e., *nap*, *sleep*, and *wake*) and window size. The window size with the highest mean accuracy values (rounded to two digits, with ties decided by the lowest window size), was selected as the window size to smooth predictions.

3.3.3.5 Model Evaluation

Leave-one-subject-out (LOSO) cross-validation was used to evaluate the predictive capacity of the Random Forest models. Each Random Forest model was trained with one participant removed from the dataset, then the one participant excluded from the training data set was used as the testing data for the created model. Thus, the number of Random Forest models trained and tested is equal to the total number of participants. Kappa scores were calculated to assess agreement for all tested models, and the strength of agreement for Kappa scores were defined as poor (<0.00), slight (0.00-0.20), fair (0.21-0.40), moderate (0.41-0.60), substantial (0.61-0.80), and almost perfect (0.81-1.00) (Landis & Koch, 1977). Confusion matrixes were created, and calculations were performed for overall accuracy as well as behaviour specific sensitivity, specificity, and balanced accuracy. Additionally, these same calculations were performed for the simplified formula. Considering logistic regression models are susceptible to overfitting (Babyak, 2004), while Random Forest models are robust to overfitting (Breiman, 2001), different cross-validation techniques were used. Specifically, instead of leave-one-subject-out cross-validation, 50% of participants were used to train the logistic model (i.e., generate coefficients and intercept) and the other 50% were used to test the simplified formula. Lastly, a random participant was selected and the time to extract all features versus the time to extract the top 10 features were tracked to descriptively compare the two techniques.

3.3.3.6 Participant-Level Behaviour Summary Variables

The average time per day spent in *nap*, *sleep*, and *wake* according to ground truth and each classification technique were calculated for each participant, after removing non-wear time (20 minutes consecutive zeros) from ground truth *wake*. Paired t-tests were then conducted to examine if *nap*, *sleep*, and *wake* estimates from the classification techniques were significantly different from ground truth for the summary variables. Cohen's d_{ave} (i.e., $d_{ave} = Mean_{diff}/([SD_{GroundTruth} + SD_{Predicted}]/2)$ scores were calculated to describe the effect size of differences between ground truth and predicted behaviours, with effect sizes interpreted as small (<0.50), medium (0.50-0.79), and large (>0.79) (Cohen, 1988).

3.4 Results

In total there were 89 participants (67.4% boys; mean age 4.5 ± 0.7 years), of which 40 had ground truth *nap* data. Overall, participants contributed 1,091,232,000 raw accelerometer observations for each axis. The distribution of ground truth accelerometer observations were 7,670 minutes of *nap*, 265,800 minutes of *sleep*, and 332,770 minutes of *wake* time (see Supplemental Figure 3.1). When raw data was used to calculate features, 606,240 minutes of accelerometer data for all 144 features were available to train models.

Testing the full feature extraction process on one random participant took 117.9 minutes. Using leave-one-subject-out cross-validation to train a Random Forest model, led to an overall prediction accuracy of 92.2% (95% Confidence Intervals: 92.1, 92.3%), and Kappa score of 0.85 for all behaviours (see Table 3.1 for a breakdown of individual behaviours). When the Random Forest predictions were smoothed with HMM, overall prediction accuracy for all behaviours improved to 96.2% (95% CI: 96.1, 96.2%), and Kappa score of 0.93. Additionally, balanced accuracy for *nap* was 99.8% in the final model (see Table 3.2).

Table 3.1: Random Forest Confusion Matrix

		Groundtruth ↓		
		Nap	*Sleep*	*Wake*
	Nap	7670	12498	9826
Predicted →	*Sleep*	0	247854	19531
	Wake	0	5448	303413

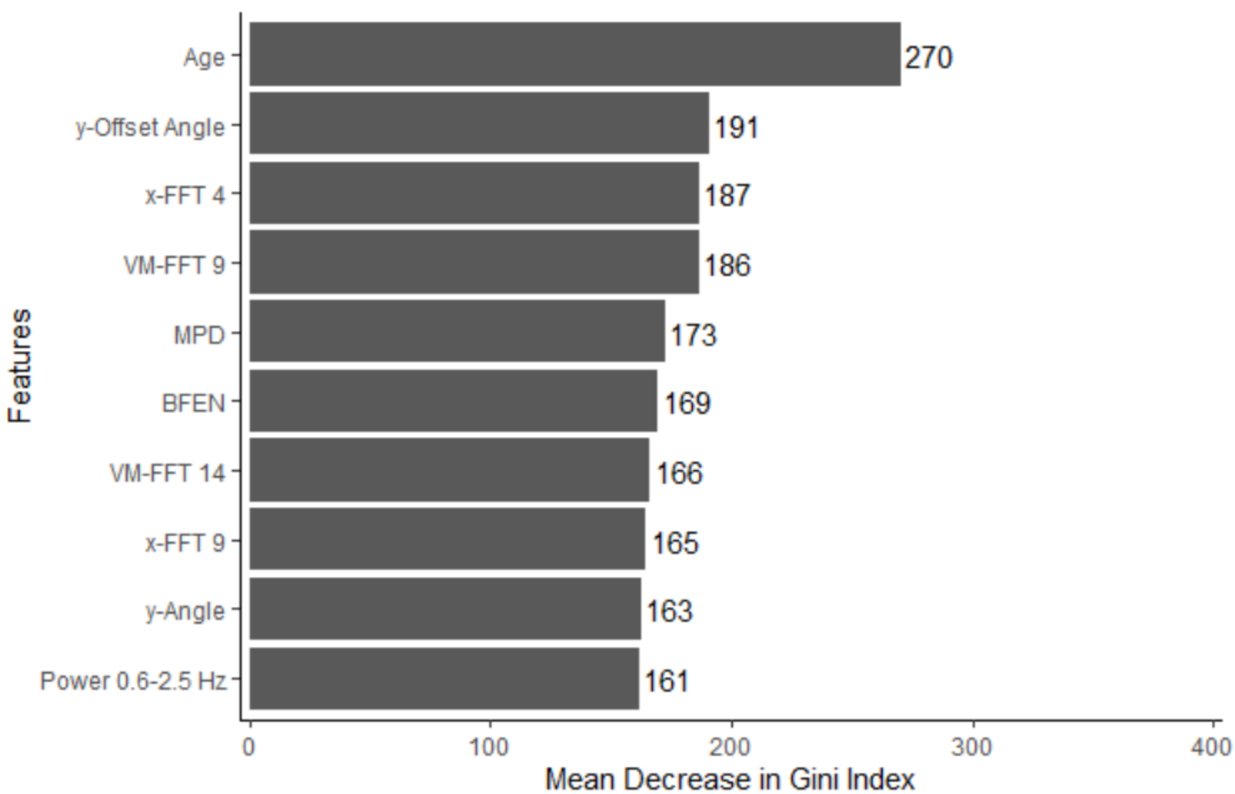
Sensitivity	100.00%	93.25%	91.18%
Specificity	96.27%	94.26%	98.01%
Balanced Accuracy	98.14%	93.76%	94.59%
All *Sleep* Accuracy		94.26%	
Overall Accuracy		92.20% (92.13-92.26%)	
Kappa		0.85	

Table 3.2: Random Forest and Hidden Markov Modeling Confusion Matrix

			Groundtruth ↓	
		Nap	*Sleep*	*Wake*
	Nap	7669	407	2375
Predicted →	*Sleep*	0	263502	18535
	Wake	1	1891	311860
	Sensitivity	99.99%	99.14%	93.72%
	Specificity	99.54%	94.56%	99.31%
	Balanced Accuracy	99.76%	96.85%	96.51%
	All *Sleep* Accuracy		96.24%	
	Overall Accuracy		96.17% (96.12-96.22%)	
	Kappa		0.93	

The top 10 variables or features in the Random Forest model, according to the mean decrease in Gini, were: 1) child's age; 2) y-axis offset angle; 3) x-axis fast fourier transformation (FFT) 4; 4) vector magnitude (VM) FFT 9; 5) mean power dispersion (MPD); 6) band pass filter (4th order Butterworth filter with $\omega 0=0.2\text{-}15.0$ Hz) followed by Euclidian norm/vector magnitude (BFEN); 7) VM FFT 14; 8) x-axis FFT 9; 9) y-axis angle relative to horizontal (y-angle); and 10) signal power at dominant frequency in 0.6-2.5 Hz range (see Figure 3.1 and Formula 1). Testing the feature extraction process on the top 10 variables for one random participant took 2.8 minutes. The threshold for maximizing sensitivity and specificity from the simplified formula, based on ROC curve analysis, was a probability value of 0.53. Thus, probabilities calculated from the simplified formula could be dichotomized with values < 0.53 classified as *wake*, and ≥ 0.53 classified as *sleep*. Using this threshold, the simplified formula led to an overall prediction accuracy of 91.3% (95% CI: 91.2, 91.4%) with a Kappa of 0.83 for all behaviours (see Table 3.3 for additional calculations). A window size of 47 minutes was selected for rolling median calculations because it had both the highest mean accuracy and the lowest size in minutes. When a 47 minute window for the rolling median was applied to the dichotomous (i.e., *sleep* vs *wake*) predictions from the simplified formula, an overall prediction accuracy was calculated as 93.7% (95% CI: 93.6, 93.7%) and Kappa as 0.87 for all behaviours (see Table 3.4 for a breakdown of individual behaviours). Additionally, *nap* classification prediction accuracy was 86.1% for the simplified formula (see Table 3.4).

Figure 3.1: Top 10 Features



Formula 1: Logistic Regression Formula for Probability of Sleep using Top 10 Features

$$p = \frac{1}{1 + b^{-(\beta_0 + \beta_1 x_1 \ldots + \beta_i x_i)}}$$

where $\beta_0 + \beta_1 x_1 \ldots + \beta_i x_i =$

(-0.88030) + (-0.03172 * Age) + (0.04979 * y-Offset Angle) + (-154.75632 * x-FFT 4) + (-502.89545 * VM-FFT 9) + (-1177.65702 * MPD) + (-20.97119 * BFEN) +

(-78.66481 * VM-FFT 14) + (126.24945 * x-FFT 9) + (-0.00406 * y-Angle) +

(71.54321 * Power 0.6-2.5 Hz)

$p \geq$ 0.53 classified as *Sleep*

Table 3.3: Logistic Regression Confusion Matrix

		Groundtruth ↓	
		Wake	*Sleep*
Predicted →	*Wake*	143006	8200
	Sleep	17429	125125
	Sensitivity	89.14%	
	Specificity	93.85%	
	Balanced Accuracy	91.49%	
	Nap Accuracy	84.57%	
	Overall Accuracy	91.28% (91.17-91.38%)	
	Kappa	0.83	

Table 3.4: Smoothed Logistic Regression Confusion Matrix

		Groundtruth ↓	
		Wake	*Sleep*
Predicted →	*Wake*	147138	5351
	Sleep	13297	127974
	Sensitivity	91.71%	
	Specificity	95.99%	
	Balanced Accuracy	93.85%	
	Nap Accuracy	86.13%	
	Overall Accuracy	93.65% (93.56-93.74%)	
	Kappa	0.87	

Using the full analytical sample (n=89), ground truth mean estimates for participant-level behaviours were 18 minutes/day for *nap*, 629 minutes/day for *sleep*, and 750 minutes/day for *wake* (Table 3.5). The mean differences between ground truth and predicted behaviours ranged from 2 to 54 minutes (absolute values). All participant-level summary variables were significantly different from ground truth estimates for machine learning models. For logistic regression predictions, all *sleep* and *wake* summaries were not significantly different from ground truth estimates, but *nap* summaries were significantly different. Cohen's d absolute values ranged from 1.94 to 0.07 and for each prediction method the average effect size could be considered small (i.e., Random Forest and HMM= 0.46, logistic=0.20, and logistic and median smoothed=0.11) or large (i.e., Random Forest=0.96).

Table 3.5: Daily Participant-Level Behaviours

Model	Behaviour	Mean (SD)	ΔMean (95% CI)	p-value	Cohen's d_{ave}
Ground Truth: Full Sample	*Nap*	18.41 (27.73)			
	Sleep	629.21 (41.67)			
	Wake	750.23 (62.43)			
Random Forest	*Nap*	72.14 (50.80)	-53.73 (-59.91, -47.55)	0.00	-1.94
	Sleep	619.82 (54.18)	9.39 (2.37, 16.41)	0.01	0.23
	Wake	705.89 (67.48)	44.34 (37.46, 51.22)	0.00	0.71
Random Forest + HMM	*Nap*	25.10 (32.81)	-6.69 (-8.42, -4.96)	0.00	-0.24
	Sleep	654.84 (45.85)	-25.63 (-30.72, -20.54)	0.00	-0.62
	Wake	717.91 (66.17)	32.32 (26.94, 37.69)	0.00	0.52
Ground Truth: Test Sample	*Nap*	17.47 (26.83)			
	Sleep	633.52 (41.01)			
	Wake	744.48 (65.39)			
Logistic	*Nap*	14.91 (24.49)	2.57 (0.82, 4.31)	0.00	0.10
	Sleep	647.04 (69.98)	-13.51 (-37.79, 10.76)	**0.27**	-0.33

	Wake	733.53 (72.92)	10.95 (-13.43, 35.32)	**0.37**	0.17
Logistic + Median Smoothed	*Nap*	15.24 (24.96)	2.24 (0.65, 3.82)	0.01	0.08
	Sleep	640.59 (70.07)	-7.07 (-31.13, 17.00)	**0.56**	-0.17
	Wake	739.65 (76.05)	4.83 (-19.28, 28.94)	**0.69**	0.07

Bolded p-values indicate no significant difference between ground truth and predicted behaviour; SD=Standard deviation; CI = Confidence interval; HMM=Hidden Markov Modeling; ΔMean = mean difference ground truth-predicted; Full Sample n=89 participants; Testing sample n=45.

3.5 Discussion

Accurately classifying sleep in preschool-aged children will improve our understanding of their 24-hour movement behaviours (Tremblay, 2019). This study used over 1 billion rows of waist-worn ActiGraph accelerometer data in preschool-aged children to classify sleep using machine learning methods. This is the first study to create a technique to classify sleep in preschool-aged children using ActiGraph accelerometers (Migueles et al., 2017). Almost perfect agreement between ground truth estimates and predictions of sleep were found for all techniques, but overall accuracy was highest when using a Random Forest classification model, smoothed with HMM. Though some differences were found between predictions of daily behaviours when compared to visual inspection.

The methods and findings of the present study are similar to a previous study that classified sleep and several types of waking activities in adults (Willetts et al., 2018). Specifically, Willets et al. (Willetts et al., 2018) achieved slightly higher balanced accuracy with 97.5% sleep classification. The small difference in accuracy between studies could reflect the more stable sleep patterns of adults compared to preschool-aged children (Carskadon & Dement, 2005). Alternatively, differences could have resulted from the ground truth measurement as Willets et al. (Willetts et al., 2018) classified sleep with self-report, while the current study used visual inspection of accelerometer data. Regardless, the difference between the findings of the two studies is nearly indistinguishable, thus the mechanisms for differences could be considered trivial.

Though almost perfect agreement was found for all sleep classification techniques when compared to ground truth visual inspection according to Kappa scores, some potentially meaningful differences were observed for summary variables. For instance, significant differences were found between ground truth visual inspection and all machine learning summaries of participants daily *nap*, *sleep*, and *wake*. However, it is important to note that the ground truth estimates of behaviours are likely not perfect so converging on 100% agreement between the two methods is very unlikely. Additionally, the agreement achieved for specific behaviours in this study were higher compared to the best practice estimates of accelerometer classification of stationary time and moderate- to vigorous-intensity physical activity in this age group (balanced accuracy range: 78-90%) (Janssen et al., 2013).

Previous studies have classified sleep in older children. For example, Smith et al. (Smith et al., 2020) classified sleep in children 5-8 years old, using the count-scaled algorithm (Galland et al., 2012), which was developed in shin-worn Actical accelerometers. Using this algorithm, waist worn ActiGraph predictions of sleep reached an overall accuracy of 88.2% (95% CI: 84.1, 91.3) (Smith et al., 2020). Results from the Random Forest and HMM in the current study had 8% higher overall accuracy. Further, Smith et al. (Smith et al., 2020) found a significant mean difference of 21 minutes between the count-scale algorithm and polysomnography estimates of overnight sleep. The differences between study results could be due to the different age groups examined. Additionally, using at-home polysomnography would give a better estimate of ground truth sleep compared to visual inspection, which could explain the improved accuracy in our study. However, the inclusion of daytime sleep in the current study, should have hypothetically lowered our accuracy estimates based on the complications of categorization of naps. Further, in a sample of school-aged children (mean age: 9.9 years), Tudor-Locke et al. (Tudor-Locke et al., 2014) modified the Sadeh algorithm and found a non-significant mean difference of 2 minutes when compared to visual inspection for nighttime sleep. Refining this algorithm in a future study yielded similar results (Barreira et al., 2015), as a non-significant mean difference of 9 minutes for nighttime sleep was found when compared to a log sheet combined with the Sadeh algorithm. Considering none of the aforementioned studies examined naps, it is not possible to contrast our results for nap classification. However, the current study found significant mean differences for all techniques and visually identified naps. Thus, future research should test a variety of methods of sleep classification in data containing naps to determine the best methods for preschool aged children.

The simplified formula created in the present study is an important contribution to the literature. While this formula still requires researchers to process raw data, which can be computationally demanding, it would greatly reduce the time required to extract features. For instance, extrapolating the results of the test participant to 100 participants, it would take 8.2 days to extract all features versus 4.7 hours for the top 10 features. However, the overall accuracy for sleep was slightly decreased using the modified formula (i.e., -2.6%), and even more of a discrepancy existed when considering naps alone (i.e., -13.6%). Though the simplified formulas were better at predicting daily behaviours, it is important to note that the logistic test sample was half the size of machine learning test samples. The smaller sample size could have led to more variability when values were summarized for each participant, which would decrease the likelihood of any meaningful differences being detected. Future research should test both methods on a larger sample to better represent the true variability of measurements. In the meantime, when computational power is a limiting factor the smoothed logistic formula is likely the best option based on less processing time and better estimates of participant-level daily behaviours. However, when computational power is not a limiting factor, the Random Forest and HMM is likely the best option based on better epoch-to-epoch accuracy.

One of the main strengths of this study is the amount of data used to train and test models. Another strength is the development of a simplified formula to classify sleep in preschool-aged children that can be used by researchers with reduced computing power. One limitation was the use of a convenience sample. Future research should attempt to apply these techniques to a randomly selected sample that is more representative of the intended population. Another limitation was the use of visual inspection as a ground truth estimate. Polysomnography is considered the gold standard for measuring sleep; however, it is not as practical for free living settings as visual inspection. Regardless, future research is needed to confirm these findings using polysomnography ground truth sleep measurements.

In conclusion, this study demonstrated almost perfect agreement between free-living visual inspection ground truth measurements and several techniques for predicting sleep in preschool-aged children wearing waist-worn ActiGraph accelerometers. This is the first study to create a technique to classify sleep in this age group using this device. Further, a simplified formula to predict sleep was created that can greatly reduce computational demands, with minor reductions in prediction accuracy. Although significant differences were found between predictions of daily behaviours when compared to visual inspection, the epoch-to-epoch accuracy of predictions is comparable to the best practice estimates of other accelerometer measured movement behaviours. Overall, the Random Forest and Hidden Markov Modeling technique appears best for sleep classification; however, the simplified formula is optimal if computing power is limited.

3.6 Supplemental Figures and Tables

Supplemental Table 3.1: Extracted Features

Feature	Source
Lux	ActiLife
Sex	Questionnaire
Age Child	Questionnaire
BFEN	GGIR
ENMO	GGIR
LFENMO	GGIR
EN	GGIR
HFEN	GGIR
HFENplus	GGIR
MAD	GGIR
anglex	GGIR
angley	GGIR
anglez	GGIR
roll med acc x	GGIR
roll med acc y	GGIR
roll med acc z	GGIR
dev roll med acc x	GGIR
dev roll med acc y	GGIR
dev roll med acc z	GGIR
ENMOa	GGIR
LFEN	GGIR
Mean	TLBC
Std	TLBC
CoefVariation	TLBC
Median	TLBC
Min	TLBC
Max	TLBC
25thP	TLBC
75thP	TLBC
Autocorr	TLBC
Corrxy	TLBC
Corrxz	TLBC
Corryz	TLBC
AvgRoll	TLBC

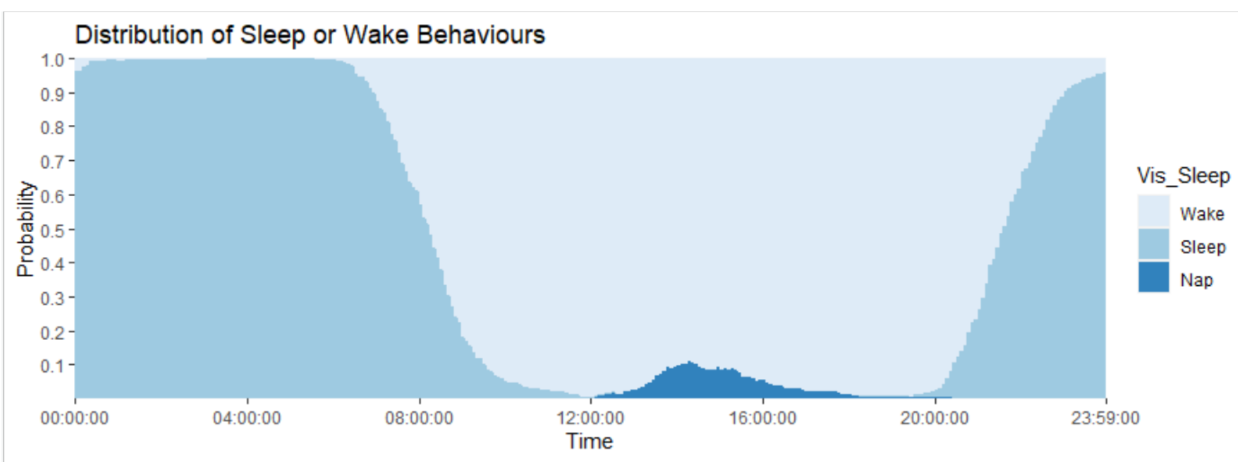
AvgPitch	TLBC
AvgYaw	TLBC
SdRoll	TLBC
SdPitch	TLBC
SdYaw	TLBC
Fmax	TLBC
Pmax	TLBC
FmaxBand	TLBC
PmaxBand	TLBC
Entropy	TLBC
VMFFT0	TLBC
VMFFT1	TLBC
VMFFT2	TLBC
VMFFT3	TLBC
VMFFT4	TLBC
VMFFT5	TLBC
VMFFT6	TLBC
VMFFT7	TLBC
VMFFT8	TLBC
VMFFT9	TLBC
VMFFT10	TLBC
VMFFT11	TLBC
VMFFT12	TLBC
VMFFT13	TLBC
VMFFT14	TLBC
xOffsetAngle	ActiGraph Inclinometer White Paper*
yOffsetAngle	ActiGraph Inclinometer White Paper*
zOffsetAngle	ActiGraph Inclinometer White Paper*
Rolling	Created for this study*
RollingOffsetAngle	Created for this study*
Kurt	Vaha-Ypya*
MAD-VY	Vaha-Ypya*
MPD	Vaha-Ypya*
Skew	Vaha-Ypya*
Meanx	Willets*
Meany	Willets*
Meanz	Willets*
Rangex	Willets*
Rangey	Willets*
Rangez	Willets*
Stdx	Willets*
Stdy	Willets*
Stdz	Willets*
xyCov	Willets*
xzCov	Willets*

yzCov	Willets*
ENMOtrunc	Willets*
xFFT0	Willets*
xFFT1	Willets*
xFFT2	Willets*
xFFT3	Willets*
xFFT4	Willets*
xFFT5	Willets*
xFFT6	Willets*
xFFT7	Willets*
xFFT8	Willets*
xFFT9	Willets*
xFFT10	Willets*
xFFT11	Willets*
xFFT12	Willets*
xFFT13	Willets*
xFFT14	Willets*
yFFT0	Willets*
yFFT1	Willets*
yFFT2	Willets*
yFFT3	Willets*
yFFT4	Willets*
yFFT5	Willets*
yFFT6	Willets*
yFFT7	Willets*
yFFT8	Willets*
yFFT9	Willets*
yFFT10	Willets*
yFFT11	Willets*
yFFT12	Willets*
yFFT13	Willets*
yFFT14	Willets*
zFFT0	Willets*
zFFT1	Willets*
zFFT2	Willets*
zFFT3	Willets*
zFFT4	Willets*
zFFT5	Willets*
zFFT6	Willets*
zFFT7	Willets*
zFFT8	Willets*
zFFT9	Willets*
zFFT10	Willets*
zFFT11	Willets*

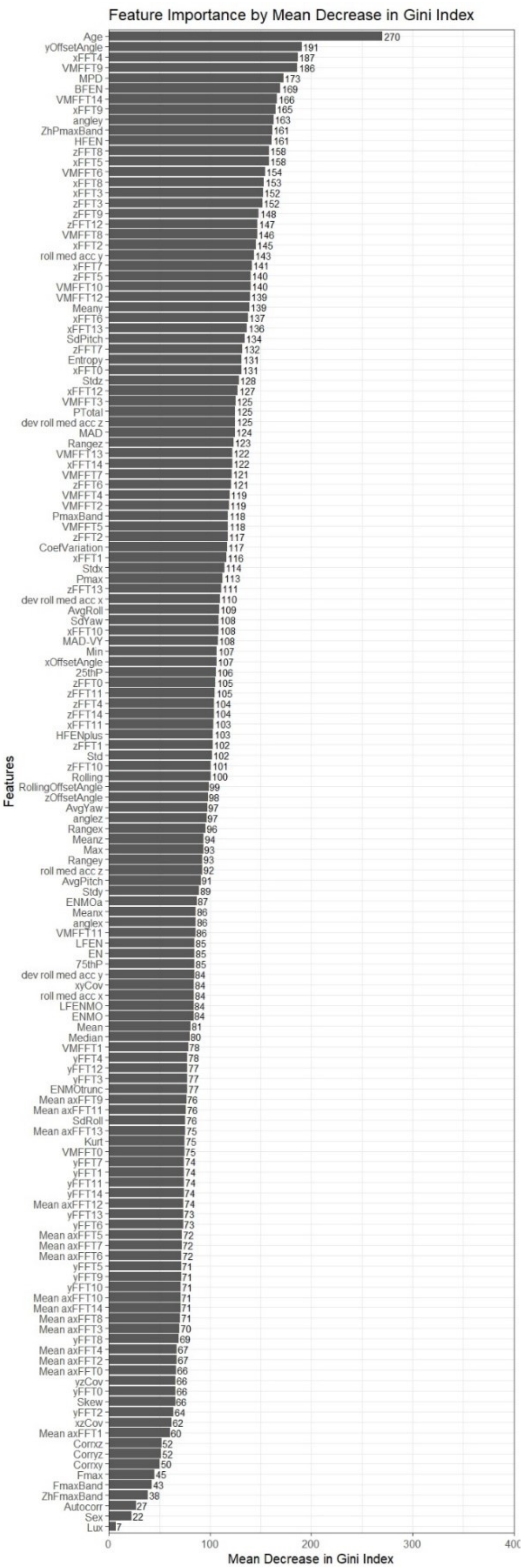
zFFT12	Willets*
zFFT13	Willets*
zFFT14	Willets*
Mean axFFT0	Willets*
Mean axFFT1	Willets*
Mean axFFT2	Willets*
Mean axFFT3	Willets*
Mean axFFT4	Willets*
Mean axFFT5	Willets*
Mean axFFT6	Willets*
Mean axFFT7	Willets*
Mean axFFT8	Willets*
Mean axFFT9	Willets*
Mean axFFT10	Willets*
Mean axFFT11	Willets*
Mean axFFT12	Willets*
Mean axFFT13	Willets*
Mean axFFT14	Willets*
PTotal	Zhang*
ZhPmaxBand	Zhang*
ZhFmaxBand	Zhang*

*Added into the TLBC::computeOneAccFeat function

Supplemental Figure 3.1:



Supplemental Figure 3.2:



3.7 References

ActiGraph Corp. (2017). ActiGraph white paper: Estimating Human Position with the ActiGraph GT3X Triaxial Activity Monitor. Retrieved from http://actigraphcorp.com/wp-content/uploads/2015/06/Inclination-White-Paper.pdf

Babyak, M. A. (2004). What You See May Not Be What You Get: A Brief, Nontechnical Introduction to Overfitting in Regression-Type Models. *Psychosomatic Medicine, 66*(3), 411-421.

Barreira, T. V., Schuna, J. M., Mire, E. F., Katzmarzyk, P. T., Chaput, J. P., Leduc, G., & Tudor-Locke, C. (2015). Identifying children's nocturnal sleep using 24-h waist accelerometry. *Medicine & Science in Sports & Exercise, 47*(5), 937-943. doi:https://dx.doi.org/10.1249/MSS.0000000000000486

Breiman, L. (2001). Random Forests. *Machine Learning, 45*(1), 5-32. doi:10.1023/A:1010933404324

Carskadon, M. A., & Dement, W. C. (2005). Normal human sleep: an overview. *Principles and practice of sleep medicine, 4*, 13-23.

Carson, V., Lee, E.-Y., Hewitt, L., Jennings, C., Hunter, S., Kuzik, N., . . . Tremblay, M. S. (2017b). Systematic review of the relationships between physical activity and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 854.

Carson, V., Tremblay, M. S., & Chastin, S. (2017f). Cross-sectional associations between sleep duration, sedentary time, physical activity, and adiposity indicators among Canadian preschool-aged children using compositional analyses. *BMC Public Health, 17*(5), 848. doi:10.1186/s12889-017-4852-0

Chaput, J.-P., Gray, C. E., Poitras, V. J., Carson, V., Gruber, R., Birken, C. S., . . . Tremblay, M. S. (2017b). Systematic review of the relationships between sleep duration and health indicators in the early years (0–4 years). *BMC Public Health, 17*(5), 855. doi:10.1186/s12889-017-4850-2

Chen, C., Liaw, A. & Breiman, L. . (2004). Using random forest to learn imbalanced data. *University of California, Berkeley*.

Cliff, D. P., Reilly, J. J., & Okely, A. D. (2009). Methodological considerations in using accelerometers to assess habitual physical activity in children aged 0-5 years. *Journal of Science and Medicine in Sport, 12*(5), 557-567. doi:10.1016/j.jsams.2008.10.008

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. New York, NY.

Ellis, K., Kerr, J., Godbole, S., Staudenmayer, J., & Lanckriet, G. (2016). Hip and Wrist Accelerometer Algorithms for Free-Living Behavior Classification. *Medicine & Science in Sports & Exercise, 48*(5), 933-940. doi:10.1249/MSS.0000000000000840

Forney, G. D. (1973). The viterbi algorithm. *Proceedings of the Institute of Electrical and Electronics Engineers, 61*(3), 268-278.

Galland, B. C., Kennedy, G. J., Mitchell, E. A., & Taylor, B. J. (2012). Algorithms for using an activity-based accelerometer for identification of infant sleep-wake states during nap studies. *Sleep Medicine, 13*(6), 743-751. doi:10.1016/j.sleep.2012.01.018

Galland, B. C., Meredith-Jones, K., Terrill, P., & Taylor, R. (2014b). Challenges and Emerging Technologies within the Field of Pediatric Actigraphy. *Frontiers in Psychiatry, 5*(99). doi:10.3389/fpsyt.2014.00099

Janssen, X., Cliff, D. P., Reilly, J. J., Hinkley, T., Jones, R. A., Batterham, M., . . . Okely, A. D. (2013). Predictive validity and classification accuracy of ActiGraph energy expenditure equations and cut-points in young children. *PLOS ONE, 8*(11), e79124. doi:10.1371/journal.pone.0079124

Kuzik, N., Poitras, V. J., Tremblay, M. S., Lee, E.-Y., Hunter, S., & Carson, V. (2017). Systematic review of the relationships between combinations of movement behaviours and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 849.

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *biometrics*, 159-174.

Mannini, A., Intille, S. S., Rosenberger, M., Sabatini, A. M., & Haskell, W. (2013). Activity recognition using a single accelerometer placed at the wrist or ankle. *Medicine & Science in Sports & Exercise, 45*(11), 2193-2203. doi:10.1249/MSS.0b013e31829736d6

Migueles, J. H., Cadenas-Sanchez, C., Ekelund, U., Delisle Nyström, C., Mora-Gonzalez, J., Löf, M., . . . Ortega, F. B. (2017). Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations. *Sports Medicine, 47*(9), 1821-1845. doi:10.1007/s40279-017-0716-0

Migueles, J. H., Rowlands, A. V., Huber, F., Sabia, S., & van Hees, V. T. (2019). GGIR: A Research Community–Driven Open Source R Package for Generating Physical Activity and Sleep Outcomes From Multi-Day Raw Accelerometer Data. *Journal for the Measurement of Physical Behaviour, 2*(3), 188. doi:10.1123/jmpb.2018-0063

Pedišić, Ž., Dumuid, D., & Olds, T. (2017). Integrating sleep, sedentary behaviour, and physical activity research in the emerging field of time-use epidemiology: Definitions, concepts, statistical methods, theoretical framework, and future directions. *Kinesiology: International journal of fundamental and applied kinesiology, 49*(2), 10-11.

Poitras, V. J., Gray, C. E., Janssen, X., Aubert, S., Carson, V., Faulkner, G., . . . Tremblay, M. (2017). Systematic review of the relationships between sedentary behavior and health indicators in the early years (aged 0-4 years). *BMC Public Health, 17*(5), 868.

Sadeh, A., Acebo, C., Seifer, R., Aytur, S., & Carskadon, M. A. (1995). Activity-based assessment of sleep-wake patterns during the 1st year of life. *Infant Behavior and Development, 18*(3), 329-337.

Smith, C., Galland, B., Taylor, R., & Meredith-Jones, K. (2020). ActiGraph GT3X+ and Actical Wrist and Hip Worn Accelerometers for Sleep and Wake Indices in Young Children Using an Automated Algorithm: Validation With Polysomnography. *Frontiers in Psychiatry, 10*, 958-958. doi:10.3389/fpsyt.2019.00958

Taylor, R. W., Haszard, J. J., Meredith-Jones, K. A., Galland, B. C., Heath, A.-L. M., Lawrence, J., . . . Taylor, B. J. (2018). 24-h movement behaviors from infancy to preschool: cross-sectional and longitudinal relationships with body composition and bone health. *International Journal of Behavioral Nutrition and Physical Activity, 15*(1), 118.

Tremblay, M. S. (2019). Introducing 24-Hour Movement Guidelines for the Early Years: A New Paradigm Gaining Momentum. *Journal of Physical Activity and Health, 1*(aop), 1-4.

Tudor-Locke, C., Barreira, T. V., Schuna, J. M., Jr., Mire, E. F., & Katzmarzyk, P. T. (2014). Fully automated waist-worn accelerometer algorithm for detecting children's sleep-period

time separate from 24-h physical activity or sedentary behaviors. *Applied Physiology, Nutrition, and Metabolism, 39*(1), 53-57. doi:10.1139/apnm-2013-0173
Vaha-Ypya, H., Vasankari, T., Husu, P., Suni, J., & Sievanen, H. (2015). A universal, accurate intensity-based classification of different physical activities using raw data of accelerometer. *Clin Physiol Funct Imaging, 35*(1), 64-70. doi:10.1111/cpf.12127
Van Cauwenberghe, E., Gubbels, J., De Bourdeaudhuij, I., & Cardon, G. (2011a). Feasibility and validity of accelerometer measurements to assess physical activity in toddlers. *International Journal of Behavioral Nutrition and Physical Activity, 8*(1), 67. doi:10.1186/1479-5868-8-67
Willetts, M., Hollowell, S., Aslett, L., Holmes, C., & Doherty, A. (2018). Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 UK Biobank participants. *Scientific Reports, 8*(1), 7961. doi:10.1038/s41598-018-26174-1
Zhang, S., Rowlands, A. V., Murray, P., & Hurst, T. L. (2012). Physical Activity Classification Using the GENEA Wrist-Worn Accelerometer. *Medicine & Science in Sports & Exercise, 44*(4), 742-748. doi:10.1249/MSS.0b013e31823bf95c
Zhang, Z., Sousa-Sá, E., Pereira, J., Chaput, J.-P., Okely, A., Feng, X., & Santos, R. (2019). Correlates of nocturnal sleep duration, nocturnal sleep variability, and nocturnal sleep problems in toddlers: results from the GET UP! Study. *Sleep Medicine, 53*, 124-132. doi:10.1016/j.sleep.2018.08.035
Zucchini, W., MacDonald, I. L., & Langrock, R. (2017). *Hidden Markov models for time series: an introduction using R*: CRC press.

4 Manuscript 2

Movement behaviours and physical, cognitive, and social-emotional development in preschool-aged children: cross-sectional associations using compositional analyses

Nicholas Kuzik, Patti-Jean Naylor, John C. Spence, Valerie Carson

4.1 Abstract

Background

Movement behaviours (e.g., sleep, sedentary behaviour, and physical activity) in isolation have demonstrated benefits to preschool-aged children's development. However, little is known on the integrated nature of movement behaviours and their relationship to healthy development in this age range. Thus, the objective of this study was to examine the relationships between accelerometer-derived movement behaviours and indicators of physical, cognitive, and social-emotional development using compositional analyses in a sample of preschool-aged children.

Methods

Children (n=95) were recruited in Edmonton, Canada. Movement behaviours were measured with ActiGraph wGT3X-BT accelerometers worn 24 hours/day. Physical (i.e., body mass index [BMI] z-scores, percent of adult height, and motor skills), cognitive (i.e., working memory, response inhibition, and vocabulary), and social-emotional (i.e., sociability, externalizing, internalizing, prosocial behaviour, and cognitive, emotional, and behavioural self-regulation) development were assessed. Objective height and weight were measured for BMI z-scores and percent of adult height, while the Test of Gross Motor Development-2 was used to assess motor skills. The Early Years Toolbox was used to assess all cognitive and social-emotional development indicators. Compositional linear regression models and compositional substitution models were conducted in R.

Results

Children accumulated 11.1 hours of sleep, 6.1 hours of stationary time, 5.1 hours of light-intensity physical activity (LPA), and 1.8 hours of moderate- to vigorous-intensity physical activity (MVPA) per day. Movement behaviour compositions were significantly associated with physical (i.e., locomotor skills, object motor skills, and total motor skills) and cognitive (i.e., working memory and vocabulary) development (R^2 range: 0.11-0.18). In relation to other movement behaviours in the composition, MVPA was positively associated with most physical development outcomes; while stationary time had mixed findings for cognitive development outcomes (i.e., mainly positive associations in linear regressions but non-significant in substitution models). Most associations for LPA and sleep were non-significant.

Conclusions

The overall composition of movement behaviors appeared important for development. Findings confirmed the importance of MVPA for physical development. Mixed findings between stationary time and cognitive development could indicate this sample engaged in both beneficial (e.g., reading) and detrimental (e.g., screen time) stationary time. However, further research is needed to determine the mechanisms for these relationships.

4.2 Introduction

Sleep, sedentary behaviour, and physical activity—collectively referred to as movement behaviours—have received increased attention for their health benefits to preschool-aged children's development (Tremblay et al., 2017c). Systematic reviews of isolated movement behaviours have concluded more sleep, more physical activity, and less sedentary behaviour have numerous health benefits to aspects of physical, cognitive, and social-emotional development in preschool aged children (Carson et al., 2017b; Chaput et al., 2017b; Poitras et al., 2017). However, considering that within a 24-hour period a change to one movement behaviour would necessitate compensation from another movement behaviour(s), the health benefits of movement behaviours in isolation may be misleading. For instance, if an intervention successfully increased a child's physical activity by 30 minutes in a day, then there would need to be 30 minutes less across the other movement behaviours. Thus, an integrated approach to understanding the health benefits of movement behaviours should be considered.

To date, little is known on the integrated nature of movement behaviours and their relation to healthy development in preschool-aged children (Kuzik et al., 2017). In a recent systematic review of 10 studies examining combinations of movement behaviours, only physical development was examined and no studies included all movement behaviours (Kuzik et al., 2017). Therefore, future research is needed on the collective relations between all movement behaviours with a broad range of developmental outcomes. Specifically, development can be categorized into three broad domains: physical (e.g., growth, motor skills, physical health), cognitive (e.g., executive functions, vocabulary), and social-emotional (e.g., emotional intelligence, relationship building) development (Berk, 2013). However, to examine the collective relations between movement behaviours and these broad domains of development, methods that appropriately consider the codependent nature of movement behaviours are needed (Kuzik et al., 2017).

Individual movement behaviours are considered codependent because they cannot co-occur (mutually exclusive) and when all individual movement behaviours are summed they will equal the total time-frame sampled (exhaustive) (Pedišić et al., 2017). Mutually exclusive and exhaustive properties of movement behaviours means this data is only meaningfully interpreted as a proportion of a whole, and thus are considered to have a constant sum constraint (values that always add to make a whole) (Aitchison, 1986). One method that is capable of appropriately handling the codependent nature of movement behaviours is compositional analyses (Chaput et al., 2014; Pedišić et al., 2017). Since the integrated movement behaviour systematic review (Kuzik et al., 2017), two studies have used compositional analyses to examine the associations between all movement behaviours and development outcomes in preschool aged children (Carson, Tremblay, & Chastin, 2017e; Taylor et al., 2018). While health benefits were found for movement behaviours in both studies, only physical development outcomes were examined (Carson et al., 2017e; Taylor et al., 2018). Given the limited evidence, further research is needed to confirm previous findings on physical development as well as address the evidence gap related to cognitive and social-emotional development. Thus, the objective of this study is to examine the relations between accelerometer-derived movement behaviours and indicators of physical, cognitive, and social-emotional development using compositional analyses in a sample of preschool-aged children.

4.3 Methods

4.3.1 Participants and procedures

Data used in this analysis were collected as part of the Parent-Child Movement Behaviours and Pre-School Children's Development study. Participants were children aged 3-5 years and their parents, whose primary language at home was English. Parents or guardians were recruited in Edmonton, Canada and surrounding areas through a local division of Sportball, a program that aims to teach children fundamental sport skills through play. Parents were approached in person by the lead investigator during Sportball summer camps and at Sportball classes. A total of 60/102 children were recruited from summer camps, but participation rates and reasons for non-participation from classes were not tracked due to logistical constraints. Additionally, the local Sportball organization distributed recruitment materials to parents via email and social media. It is unknown how many eligible parents received the email or viewed the social media posts, or their reasons for non-participation. In total, 131 parents or guardians agreed to participate. Ethical approval was obtained from the University of Alberta Research Ethics Board (Study ID: Pro00081175). Parents or guardians provided written informed consent

Data collection for this cross-sectional study occurred from July to November 2018. Children's gross motor development was measured at the University of Alberta. After the motor development assessment, parents and children were provided accelerometers, verbal and written study protocol instructions, and a log sheet to track sleep and accelerometer wear time. After the accelerometer wear period, the lead investigator visited the homes of parents or an alternative preferred location (n=2) to collect the accelerometers. During the home visit, parents completed a questionnaire, which included the social-emotional development measures and socio-demographic measures, while children were administered cognitive development tasks.

Additionally, children's height and weight were measured, and parents' height was also measured if they wanted assistance reporting their height in the questionnaire.

4.3.2 Measures

4.3.2.1 Movement behaviours

The children's movement behaviours included total sleep, stationary time [i.e., sedentary behaviour categorization in accelerometer data that contains no posture detection (Tremblay et al., 2017a)], light-intensity physical activity (LPA), and moderate- to vigorous-intensity physical activity (MVPA). All movement behaviours were measured with ActiGraph WGT3X-BT accelerometers that were programmed at 30 Hz and given to a child and one parent. While 90-100 Hz is the recommended frequency for ActiGraph accelerometers in preschool-aged children, we chose 30 Hz to align with the validation studies that our movement behaviour cut-points are based on (Migueles et al., 2017). In nine cases, multiple preschool-aged children from the same family participated. Parents and children were instructed to wear the accelerometer on an elastic belt on their right hip for 24 hours a day over 7 days, except during water-based activities. Accelerometers were programmed to begin recording at the next instance of 00:00:00. When accelerometers were collected, data were downloaded in 15-second epochs for both normal filter files and low frequency extension (LFE) filter files. Normal filtered files were used to categorize children's stationary time (≤25 counts/15 seconds), LPA (26-419 counts/15 seconds), and MVPA (≥420 counts/15 seconds), while LFE files were used to categorize total sleep (Hjorth et al., 2012). While using shorter epochs may be advantageous to better represent the sporadic movement profiles of preschool-aged children, 15-second epochs were used to align with the validation studies that our movement behaviour cut-points are based on (Migueles et al., 2017). All movement behaviour categorization was conducted in R (version 3.6.1). For sleep, daytime (e.g., nap) and nighttime sleep were categorized through visual inspection guided by the log book, and heuristics according to previous visual inspection literature (Tudor-Locke et al., 2014). Sleep data was then merged with the normal filtered file, and non-wear time (i.e., >20 minutes consecutive 0 counts, no interruptions) was removed that was not sleep. Finally, days with <10 hours/day of waking day wear time were removed and participants with <3 days were removed.

4.3.2.2 Physical development

Physical development was operationalized as motor skills, adiposity, and growth. Motor skills were measured with the Test of Gross Motor Development – 2nd Edition (TGMD-2). Heights and weights were measured to calculate the surrogate adiposity measure of body mass index (BMI) z-scores. Growth was measured with heights, which were used to calculate child's percent of expected adult height.

The TGMD-2 assessed object skills, locomotor skills, and total motor skills. Testing consisted of six object motor skills (i.e., striking a stationary ball, dribbling, kicking, catching, overhand throwing, and underhand rolling) and six locomotor skills (i.e., running, galloping, hopping, leaping, horizontal jumping, and sliding) (Ulrich, 2000). Children were divided into groups with one to five children in each group. Groups rotated around three to four stations that each had three to four skills and two different research team members. At each station, one team member took on the role of the facilitator while the other took on the role of the assessor. The facilitators main task was demonstrating and verbally explaining the skill two times for the children. Then each child was given one chance to practice the skill and two scored trials for each skill. The assessors main task was live scoring the children's attempts at performing the skill, as well as wearing a body camera that recorded a video of children's assessments to be scored later. All 12 skills were composed of three to five components, which were scored as demonstrated (i.e., 1) or not demonstrated (i.e., 0). Scores for both trials were summed across components to create an object motor skill score and a locomotor skill score, both out of a maximum 48 points. Object and locomotor skill scores were then summed to create a total motor development score. For each child, live scores coded by assessors and video scores coded by the lead investigator were compared for all pair-wise complete observations. Intraclass correlation coefficients (ICC; two-way, agreement) indicated moderate to good agreement for object motor (ICC = 0.719; 95% Confidence Interval (CI): 0.340, 0.860), locomotor (ICC = 0.693; 95% CI: 0.423, 0.825), and total motor skills (ICC = 0.791; 95% CI: 0.277, 0.915). Since live scores were scored by multiple assessors and video scores were scored by one assessor, video scored values were used for analysis. However, when a video score was missing, live scores were used for that observation. A recent systematic review of the TGMD-2 found several studies demonstrating moderate-strong criterion validity (e.g., r: 0.49-0.63 when compared to other motor development assessments), as well as excellent test-retest (ICC: 0.81-0.92), inter-rater (ICC: 0.88-0.93), and intra-rater reliability (ICC: 0.92-0.99) (Griffiths et al., 2018).

Children's height and weight were each measured twice with a stadiometer and digital scale, respectively. Children's weight was measured to the nearest 0.1 kg and height was measured to the nearest 0.1 cm. If a difference of ≥0.3 units were scored between the two measurements, a third measurement was performed and the average of the two closest measurements were used. Body mass index (BMI) z-scores were calculated according to the World Health Organization's (WHO) growth standards (World Health Organization Multicentre Growth Reference Study Group, 2006).

Children's height was measured with stadiometer as described above. The height of both biological parents was reported in the parental questionnaire. Parents also had the option to have their height measured with the stadiometer at the home visit so they could enter that value into the questionnaire. The child's current percent of expected adult height was calculated based on their current height and the average of their biological mother's and father's height, according to sex specific formulas (Luo, Albertsson-Wikland, & Karlberg, 1998b).

4.3.2.3 Cognitive development

Response inhibition, visual-spatial working memory, and language development were employed as indicators of cognitive development. Based on pre-existing protocols (Case, 1985; Howard & Okely, 2015; Morra, 1994; Wiebe, Sheffield, & Espy, 2012), they were measured using the iPad-based Early Years Toolbox (Howard & Melhuish, 2017). As parts of the toolbox, the Go/No-Go task was used to test response inhibition, the Mr. Ant task was used to test visual-spatial working memory, and the Expressive Vocabulary task was used to test language development. Visual and auditory instructions are built into each iPad task in order to standardize administration, however the lead investigator was also trained to provide further supplementary information when the child required clarification.

For the Go/No-Go task (Howard & Okely, 2015; Wiebe et al., 2012), children were required to tap the screen when they saw a fish, which occurs 80% of the time (Go) but not tap the screen when they saw a shark, which occurs the remaining 20% of the time (No-Go). There were a total of three trials completed for all children with no changes in complexity. For each trial, 75 stimuli (fish or sharks) were presented in a semi-random order (i.e., no trial begins with a shark, and sharks are not presented consecutively more than twice) for 1,500 milliseconds followed by 1,000 milliseconds of no stimulus. Scores were calculated by multiplying the proportion of correct Go and No-Go stimuli (e.g., 160/180 correct Go stimuli multiplied by

30/45 correct No-Go stimuli = 0.593), with values closer to 1 indicating better response inhibition.

For the Mr. Ant task (Case, 1985; Morra, 1994), children saw Mr. Ant with sticker(s) (n=1-8) on different parts of his body for 5 seconds, a blank screen for 4 seconds, and Mr. Ant again with auditory prompt to place stickers back on Mr. Ant. The task progressed in levels (n=1-8 stickers) with three trials for each level to a maximum of 8 levels, and correspondingly a maximum of 8 points. The task ended after failure on all three trials within a level or successful completion of all eight levels. Starting at level 1, points were calculated as 1 point for each level with at least 2/3 trials correct. After a level was scored as 1/3 correct trials, that level and all subsequent levels were scored based on the number of correct trials, with 1/3 of a point for each correct trial.

For the Expressive Vocabulary task, children were presented with a maximum of 45 pictures and they were instructed to tell the lead investigator what the picture was. An incorrect description of the picture prompted the lead investigator to ask what else the item could be called, until the child correctly described the picture or until the lead investigator was confident that the child could not correctly produce the required word. Six incorrect descriptions in a row stopped the test, and points were calculated by summing the number of correct words.

The Early Years Toolbox has previously shown good to excellent reliability (Cronbach's α range: 0.84 - 0.95) for the internal consistency of response inhibition and expressive vocabulary, and moderate-strong criterion validity (r: 0.40-0.60) for the correlations between response inhibition, visual-spatial working memory, and expressive vocabulary with other validated tasks from the National Institute of Health's Toolbox and British Ability Scales (Howard & Melhuish, 2017). In the present study, acceptable-good internal consistency reliability (Terwee et al., 2010) was observed for go trials (Cronbach's $\alpha = 0.90$), no-go trials (Cronbach's $\alpha = 0.78$), and expressive vocabulary (Cronbach's $\alpha = 0.90$).

4.3.2.4 Social-emotional development

Sociability, externalizing, internalizing, prosocial behaviour, and self-regulation (i.e., cognitive, emotional, and behavioural self-regulation) were the social-emotional development indicators used in this study. Social-emotional development was measured using the paper-based Child Self-Regulation and Behaviour Questionnaire (CSBQ), which is also part of the Early Years Toolbox (Howard & Melhuish, 2017). Parents completed 34-items, with responses ranging from 1 (not true) to 5 (certainly true). Subscales were calculated by averaging scores across items, while reverse scoring some items. Each subscale ranged from 1 to 5, with values closer to 5 being favourable for sociability, prosocial behaviour, and self-regulation, while values closer to 1 were favourable for internalizing and externalizing. When data was missing (n=7), subscale averages were calculated without the missing items.

A previous study that used the first iteration of the questionnaire, with changes mainly consisting of going from 33 to 34 items in the current version, found that all subscales of the CSBQ had acceptable-good reliability (Cronbach's α range: 0.74-0.89) for internal consistency, and moderate-very strong correlations (r: 0.48 - 0.91) for analogous and nearest comparisons with Strengths and Difficulties Questionnaire subdomains (Howard & Melhuish, 2017). In the present study, good internal consistency reliability (Terwee et al., 2010) was observed for most subscales (Cronbach's α: 0.75-0.82), except for internalising (Cronbach's $\alpha = 0.55$) and prosocial behaviour (Cronbach's $\alpha = 0.64$).

4.3.2.5 Covariates

Based on previous movement behaviour and development research (Carson et al., 2017a; Carson & Kuzik, 2017), children's age, sex, ethnicity, number of siblings, and hours of childcare attendance, as well as parental age, relation to the child, education, income, marital status, type of home, and size of yard were considered as covariates. Child and parent age, on the day they received accelerometers, were calculated based on their date of birth reported on consent forms and questionnaires. Parent's were asked to select their "child's race/ethnicity (check all that apply)" from a list of 13 responses, and for analysis children were categorized as "White" or "underrepresented groups" due to the high prevalence of "Caucasian" responses, and heterogeneity across the other 12 possible response options. Number of siblings was scored ranging from "0" to "≥3" younger and older siblings, and classified as "0", "1", "≥2" total siblings. Childcare attendance was determined by asking parents in the questionnaire how many hours/week their child typically spends in care other than their own. Parental relationship to the child (i.e., "mother", "father", "other") was classified as "mother" or "father" since no one in this analytical sample selected "other". Seven response options for parental education ranged from "Less than high school diploma or its equivalent" to "University certificate, diploma, or degree above the bachelor's level". Parental income was based on 10 response options ranging from "Less than $25,000" to "More than $200,000" that increased by $25,000 at each choice, as well as a "Do not know" option. Two participants responded, "Do not know" and their responses were imputed to the sample median. Marital status was classified as "married" or "not married" because of the high prevalence of married responses and the heterogeneity across the other five possible response options. Home type was classified as "one level" or "two levels" based on nine possible response options, and an "other" response option where participants could specify their home type. Five response options for size of parent's yard ranged from "No yard at all" to "A large yard (e.g., ¼ acre block or larger)".

4.3.3 Data analysis

Standard descriptive statistics were calculated for all outcome (physical=5, cognitive=3, social-emotional=7) and demographic variables. Compositional descriptive statistics were calculated for the centrality and dispersion of movement behaviour data (Van den Boogaart & Tolosana-Delgado, 2013). Centrality was defined by the closed geometric mean of all movement behaviours, normalized to 24-hours. Dispersion was calculated with a variation matrix that demonstrates the proportionality between two movement behaviours, with values closer to zero indicating a higher codependence.

Isometric log ratio transformations of the composition of movement behaviours (i.e., total sleep, stationary time, LPA, and MVPA) were calculated (Van den Boogaart & Tolosana-Delgado, 2013). Regression models with only movement behaviour composition variables and outcome variables were created to determine the overall influence of the composition of movement behaviours on each outcome variable. The coefficient of determination (R^2) indicated the effect size for the relation between movement behaviour compositions and the outcome variables. Next, simple linear regression models were conducted between each potential covariate and each outcome variable. Covariates were only included if they were significant in the simple linear regression models, such that each final model would only include covariates relevant to a particular outcome. Final models were then created for each outcome variable that included the pivot coordinates of isometric log ratio transformed movement behaviour compositions and covariates. The first pivot coordinate of each movement behaviour composition was considered to represent the influence of a single movement behaviour, in relation to the rest of the composition of movement behaviours, on each outcome variable.

Compositional substitution or time reallocation analyses were conducted according to methods proposed by Dumuid and colleagues (2019). Briefly, this analysis subtracts the predicted value of the outcome variable of the base regression model, from updated models that alter the movement behaviour composition variables according to a substitution of one movement behaviour for another movement behaviour. In total, 12 substitution models (e.g., reallocating 30 minutes of MVPA with 30 minutes of sleep) were created and compared to the base model, for each outcome variable. All substitutions looked at the change in outcome variables when 30 minutes of one movement behaviour was substituted for 30 minutes of another behaviour. To ensure that 30 minutes substitutions were plausible, the minimum amount of MVPA a participant accumulated (i.e., 47 minutes), as well as 1 standard deviation for time spent in MVPA (i.e., 28.8 minutes/day) were considered.

Assumptions for regression analyses (i.e., linearity, normality, and equal variance of residuals, as well as identifying influential observations) were checked through visual inspection of residuals (i.e., residuals vs fitted values, Q-Q, square root of Standardized residuals vs. fitted values, and Cook's Distance) and Shapiro-Wilk test of normality. Models with sociability, externalizing, internalizing, BMI, and total motor skills were significant in Shapiro-Wilk tests indicating multivariate non-normality. Transformations could not be completed for time reallocation models because they would disrupt the interpretation of results. Additionally, for other models, numerous transformations were applied to these outcomes and normality was not reached. Thus, participants were removed according to Cook's d values >4/n (Belsley, 1980) and models were re-run as sensitivity analyses to determine if findings changed. All analyses were conducted in R (version 3.6.1) and statistical significance was set at $p < 0.05$.

4.4 Results

From 131 participants, a total of 95 participants had usable accelerometer data and were included in the analysis (see Figure 4.1 for participant flow diagram). Aside from the analysis of response inhibition (n=93; n=2 software errors) and all motor skills outcomes (n=93, n=2 children chose not to participate), these 95 participants had data for all outcome variables. Children were predominantly boys (69.5%) with an average age of 4.5 years, and the average age for parents was 37.8 years (see Table 4.1 for participant characteristics). For the closed geometric mean of movement behaviours normalized to 24-hours, children accumulated 11.1 hours of sleep, 6.1 hours of stationary time, 5.1 hours of LPA, and 1.8 hours of MVPA. Additionally, the variation matrix values ranged from 0.15 (stationary time and MVPA), indicating the lowest co-dependence, to 0.02 (sleep and LPA), indicating the highest co-dependence between variables (see Table 4.2).

Figure 4.1: Participant Flow Diagram

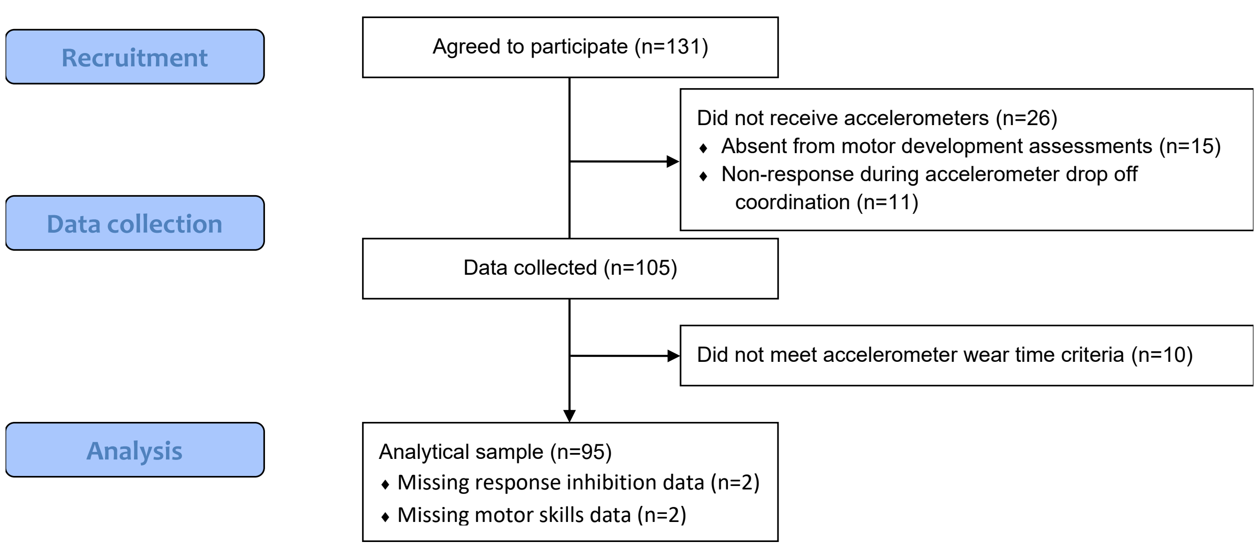


Table 4.1: Outcome and Covariate Descriptive Information

Outcome Variable	Mean/Mode (SD/Percent)	Covariate Variable	Mean/Mode (SD/Percent)
Locomotor Skills	27.8 (8.7)	Child Age (years)	4.5 (0.7)
Object Motor Skills	23.1 (7.1)	Sex	Male (69.5%)
Total Motor Skills	50.9 (13.8)	Childcare (hours/week)	21.2 (17.5)
BMI z-scores	0.2 (0.9)	Ethnicity	Caucasian (71.6%)
Expected Adult Height (%)	60.6 (3.8)	Siblings	One (54.7%)
Response Inhibition	0.6 (0.2)	Parent Age (years)	37.5 (5.1)
Working Memory	1.9 (0.9)	Parent Education	Bachelor's degree (49.5%)
Vocabulary	30.9 (7.2)	Parent Relation to Child	Mother (81.1%)
Behavioural Self-Regulation	3.9 (0.7)	Marital Status	Married (89.5%)
Cognitive Self-Regulation	3.7 (0.6)	Household Income	> $200,000 (25.3%)
Emotional Self-Regulation	3.4 (0.8)	Home Type	Two levels (61.1%)
Externalizing	2.1 (0.8)	Yard Size	Medium yard (69.5%)
Internalizing	1.3 (0.4)		
Sociability	4.0 (0.7)		
Prosocial Behaviour	4.0 (0.6)		

BMI=Body mass index

Table 4.2: Movement Behaviour Geometric Mean (closed to 24 hours) and Variation Matrix

	LPA	MVPA	Sleep	Stationary
Mean (hours/day)	5.09	1.75	11.12	6.05
LPA Variation	0			
MVPA Variation	0.07	0		
Sleep Variation	0.02	0.10	0	
Stationary Variation	0.05	0.15	0.04	0

LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; Stationary= Stationary time. Values closer to zero indicate higher codependence.

The composition of movement behaviours were significantly associated with three physical development outcomes (i.e., locomotor skills, object motor skills, and total motor skills) and two cognitive development outcomes (i.e., working memory and vocabulary) (see Table 4.3). For all significant models, R^2 values were above 0.09 (Range: 0.11, 0.16) indicating medium effect sizes (Cohen, 1977). Covariates that were significantly associated across outcome variables and included in final regression models were: children's age, sex, ethnicity, number of siblings, as well as parental age, income, marital status, type of home, and size of yard (see Table 4.4 for all significant relations). Child's age was the most frequently included covariate in 7/15 of the final regression models, with parent's age and child sex being the next most frequently included with 3/15 models (see Table 4.4).

Table 4.3: Outcome and Movement Behaviour Composition Full Models

Domain	Outcome Variable	R^2	p value
Physical†	Locomotor Skills	0.11	0.02*
	Object Motor Skills	0.18	0.00*
	Total Motor Skills	0.16	0.00*
	BMI z-scores	0.05	0.22
	Expected Adult Height (%)	0.04	0.30
Cognitive†	Response Inhibition	0.08	0.07
	Working Memory	0.11	0.01*
	Vocabulary	0.16	0.00*
Social-Emotional	Behavioural Self-Regulation	0.00	0.98
	Cognitive Self-Regulation	0.06	0.15
	Emotional Self-Regulation	0.01	0.90
	Externalizing	0.01	0.74
	Internalizing	0.04	0.32
	Sociability	0.08	0.05
	Prosocial Behaviour	0.00	0.97

†= Movement behaviour compositions were significantly associated with the majority of outcome variables for the developmental domain (i.e., physical: 3/5; cognitive: 2/3; social-emotional: 0/7); *= significant at $p < 0.05$

Table 4.4: Significant Outcome and Covariate Regression Models

Domain	Outcome	Covariate	Beta (p-value)
Physical	Locomotor Skills	Child Age (years)	5.24 (0.00)
	Object Motor Skills	Child Age (years)	3.58 (0.00)
	Total Motor Skills	Child Age (years)	8.82 (0.00)
	BMI z-scores	Home Type (two levels)	-0.46 (0.01)
	Expected Adult Height (%)	Child Age (years)	0.04 (0.00)
		Sex (female)	0.03 (0.00)
		Parent Age (years)	0.00 (0.04)
		Household Income ($)	0.01 (0.01)
Cognitive	Response Inhibition	Child Age (years)	0.11 (0.00)
		Sex (female)	0.12 (0.01)
	Working Memory	Child Age (years)	0.60 (0.00)
	Vocabulary	Child Age (years)	6.79 (0.00)
		Parent Age (years)	0.33 (0.02)
		Marital Status (not married)	-5.16 (0.03)
Social-Emotional	Cognitive Self-Regulation	Parent Age (years)	0.03 (0.03)
	Emotional Self-Regulation	Siblings (≥ 2)	-0.55 (0.03)
	Internalizing	Ethnicity (non-Caucasian)	-0.19 (0.04)
	Sociability	Yard Size (increasing size)	-0.26 (0.00)
	Prosocial Behaviour	Sex (female)	0.26 (0.04)
		Siblings (≥ 2)	-0.41 (0.02)
		Yard Size (increasing size)	-0.19 (0.01)

Child age, parent age, household income, and yard size were treated as continuous variables and their unit is listed in parentheses; Home type, sex, marital status, siblings and ethnicity were treated as categorical variables and their comparator is listed in parentheses.

Within compositional linear regression models, 5/20 significant relationships were found for physical development, 2/12 significant relationships were found for cognitive development, and 1/28 significant relationships were found for social-emotional development (see Table 4.5). For physical development, MVPA, relative to the other movement behaviours in the composition, was positively associated with object, locomotor, and total motor skills. While LPA, relative to the other movement behaviours in the composition, was negatively associated with object and total motor skills. For cognitive development, stationary time, relative to the other movement behaviours in the composition, was positively associated with response inhibition and vocabulary. For social-emotional development, MVPA, relative to the other movement behaviours in the composition, was positively associated with sociability. When removing multivariate influencers according to Cook's d, stationary time was significantly and negatively associated with BMI z-scores (n=89), and MVPA was significantly and negatively associated with internalizing (n=90).

Table 4.5: Compositional Linear Regressions

Outcome	LPA	MVPA	Sleep	Stationary
Physical Development				
Locomotor Skills	-14.54 (0.07)	9.05 (0.02)*	-3.80 (0.65)	9.30 (0.10)
Object Motor Skills	-14.28 (0.02)*	12.44 (0.00)*	2.37 (0.72)	-0.54 (0.90)
Total Motor Skills	-28.82 (0.02)*	21.49 (0.00)*	-1.43 (0.91)	8.76 (0.29)
BMI z-scores	-1.07 (0.20)	0.65 (0.11)	1.07 (0.20)	-0.65 (0.24)⊖
Expected Adult Height (%)	-0.02 (0.48)	0.00 (0.79)	0.02 (0.37)	-0.01 (0.59)
Cognitive Development				
Response Inhibition	-0.10 (0.61)	0.08 (0.43)	-0.26 (0.22)	0.27 (0.047)*
Working Memory	0.88 (0.24)	-0.33 (0.37)	-1.33 (0.10)	0.78 (0.14)
Vocabulary	-4.44 (0.41)	2.96 (0.25)	-8.56 (0.13)	10.04 (0.01)*
Social-Emotional Development				
Behavioural Self-Regulation	-0.10 (0.89)	-0.07 (0.84)	0.24 (0.73)	-0.07 (0.88)
Cognitive Self-Regulation	-1.18 (0.05)	0.52 (0.07)	0.48 (0.42)	0.17 (0.67)
Emotional Self-Regulation	0.89 (0.28)	-0.14 (0.72)	-0.53 (0.51)	-0.21 (0.70)
Externalizing	-0.71 (0.36)	0.37 (0.33)	-0.00 (1.00)	0.34 (0.51)
Internalizing	-0.04 (0.92)	-0.20 (0.32)⊖	0.13 (0.75)	0.11 (0.67)
Sociability	-0.64 (0.32)	0.71 (0.02)*	-0.08 (0.91)	-0.00 (1.00)
Prosocial Behaviour	-0.50 (0.36)	0.31 (0.26)	-0.22 (0.67)	0.42 (0.26)

LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; Stationary= Stationary time; *= significant at $p < 0.05$; ⊕=Became positively associated when removing influential participants according to Cook's d values >4/n; ⊖=Became negatively associated when removing influential participants according to Cook's d values >4/n

Movement behaviour reallocations were associated with four outcome variables for physical development (i.e., BMI z-scores, object, locomotor, and total motor skills), one outcome variable for cognitive development (i.e., vocabulary), and two outcome variables for social-emotional development (i.e., cognitive self-regulation and sociability) (see Table 4.6 [oversized table at the end of this manuscript]). For physical development, positive relationships were found when reallocating 30 minutes of another movement behaviour with 30 minutes of MVPA for BMI z-scores, object, locomotor, and total motor skills. Additionally, positive relationships were seen when reallocating LPA with stationary time for locomotor and total motor skills. For cognitive development, positive relationships were seen when reallocating sleep with stationary time for vocabulary. For social-emotional development, positive relationships were seen when reallocating another behaviour with MVPA for sociability and cognitive self-regulation. When removing multivariate influencers according to Cook's d, reallocating 30 minutes of MVPA with stationary time was significantly and positively associated with internalizing (n=90).

4.5 Discussion

The objective of this study was to examine the relations between accelerometer-derived movement behaviours and indicators of physical, cognitive, and social-emotional development using compositional analyses in a sample of preschool-aged children. Broad patterns for relations between movement behaviours and physical and cognitive development emerged across all analyses. However, associations with social-emotional development were less apparent. A summary of findings are presented in Tables 4.3 and 4.7 (Table 4.7 is an oversized table found at the end of this manuscript).

For physical development, mainly motor development, a number of significant associations were observed for MVPA, relative to other movement behaviours, within linear regression and substitution models. However, relations for the other movement behaviours were predominantly null. For instance, reallocating 30 minutes of LPA with 30 minutes of MVPA resulted in higher locomotor and object motor skills by 3.28 and 3.99 units, which for a child aged 4.52 years (sample mean) would mean going from the 37th percentile to the 50th percentile of locomotor skills scores, and the 37th percentile to the 50th percentile (boys) or 63rd percentile (girls) of object motor skills (Ulrich, 2000). This is line with a recent systematic review that found consistent positive relations between MVPA in isolation and motor development (Carson et al., 2017b). In contrast, LPA was negatively associated with motor skills in regression models and substitution models that reallocated stationary time with LPA. Future research is needed with tools that more accurately distinguish between sedentary behaviours and LPA in a larger more generalizable sample to better understand how these parts of the movement behaviour composition impact motor skills.

Beyond motor development, two other cross-sectional studies have used compositional analyses to examine the associations between movement behaviours and physical development in preschool children (Carson et al., 2017e; Taylor et al., 2018). For instance, the composition of movement behaviours was associated with BMI z-scores but not waist circumference (Carson et al., 2017e). Additionally, individual movement behaviours, relative to the other movement behaviours, did not demonstrate any significant relations. In another study, reallocating LPA and stationary time with sleep were all favourably associated with BMI z-scores at 3.5 years of age, while MVPA reallocations were not associated with BMI z-scores (Taylor et al., 2018). In contrast, findings from the current study suggest that reallocating stationary time with MVPA increased BMI z-scores by 0.2, and vice-versa. Previous research has shown that MVPA contributes to increased fat free mass and bone mass in preschool aged children (Butte et al., 2016; Leppänen et al., 2016; Taylor et al., 2018), so the high volume of MVPA in this sample could be contributing to increased BMI z-scores through these mechanisms.

For cognitive development, stationary time, relative to other movement behaviours, was associated with two out of three indicators of cognitive development in linear regression models. However, mainly null findings were observed for other movement behaviours in linear regression models. While three substitutions involving stationary time indicated it was favourable for vocabulary scores, overall stationary time substitutions were predominantly null for cognitive development. Similarly, substitution models for other movement behaviours with cognitive development were all null. Since stationary time can only indicate low or no movement, and not what is qualitatively occurring during this time (e.g., screen time, time spent with parents reading, standing time), extrapolating the mechanism behind the favourable associations between stationary time and cognitive development in this sample is difficult. Previous systematic reviews that examined the health implications of sedentary behaviour in isolation found that parents reading with their children had beneficial associations with cognitive development, while screen time had unfavourable associations (Poitras et al., 2017). Therefore, one possible mechanism could be that children were engaging in more stationary time that was beneficial for cognitive development (e.g., reading) as opposed to stationary time that was unfavourable for cognitive development (e.g., screen time).

These results suggest that the composition of movement behaviours, measured with accelerometers, are important for some indicators of children's development. Determining the optimal levels in a 24-hour period of these behaviours is of high importance for public health recommendations. Similar to previous research using receiver operating characteristic curves to determine the ideal amount of MVPA, vigorous-intensity physical activity (VPA), and stationary time to distinguish between obese and non-obese children (Katzmarzyk et al., 2015), future research could extend these findings and attempt to determine the optimal level of movement behaviours for healthy growth and development. However, in doing so, researchers should consider analyses sensitive to the compositional nature of all movement behaviours in a sample large enough to provide a wide spectrum of compositions.

Strengths of this study include the measurement of all movement behaviours via 24-hour wear time accelerometry, a broad array of developmental outcome measures, and the use of analyses sensitive to the compositional nature of movement behaviours. A limitation is the cross-sectional study design that prohibits understanding the causal mechanisms of the relationships observed. Additionally, the analytical sample was relatively small (n=95) and only powered to detect medium-large effect sizes in models with <3 covariates, and large effect sizes in models with ≥3 covariates (i.e., percent of expected adult height, vocabulary, and prosocial behaviour). Lastly, convenience sampling from a physical activity program could have limited our generalizability. In fact, the average minutes/day of MVPA in this sample was 40 minutes higher compared to the national average, which could suggest poor generalizability to the broader population of Canadian preschool aged children (Carson et al., 2017e).

In summary, this study used compositional analyses to examine the relations between movement behaviours across all domains of development (i.e., physical, cognitive, and social-emotional). The overall composition of movement behaviors appeared important for development. Broadly, MVPA was favourably associated with physical development, while mixed findings for stationary time indicated favourable or non-significant associations with cognitive development. Previous research has also demonstrated clear trends for favourable associations between MVPA and physical development—mainly motor development. Mixed findings between stationary time and cognitive development may indicate the inability of accelerometer research to distinguish between beneficial (e.g., reading) and detrimental (e.g., screen time) stationary time.

4.6 References

Aitchison, J. (1986). *The statistical analysis of compositional data*: Chapman & Hall, Ltd.

Belsley, D. A., Edwin Kuh, and Roy E. Welsch. (1980). Detecting Influential Observations and Outliers *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity* (pp. 6-84). New York: John Wiley.

Berk, L. E. (2013). *Development through the lifespan* (6 ed.). Boston, MA: Pearson.

Butte, N. F., Puyau, M. R., Wilson, T. A., Liu, Butte, Nancy, F., . . . Issa, F. (2016). Role of physical activity and sleep duration in growth and body composition of preschool-aged children. *Obesity, 24*(6), 1328.

Carson, V., Hesketh, K. D., Rhodes, R. E., Rinaldi, C., Rodgers, W., & Spence, J. C. (2017a). Psychometric Properties of a Parental Questionnaire for Assessing Correlates of Toddlers' Physical Activity and Sedentary Behavior. *Measurement in Physical Education and Exercise Science, 21*(4), 190-200. doi:10.1080/1091367X.2017.1322087

Carson, V., & Kuzik, N. (2017). Demographic correlates of screen time and objectively measured sedentary time and physical activity among toddlers: a cross-sectional study. *BMC Public Health, 17*(1), 187. doi:10.1186/s12889-017-4125-y

Carson, V., Lee, E.-Y., Hewitt, L., Jennings, C., Hunter, S., Kuzik, N., . . . Tremblay, M. S. (2017b). Systematic review of the relationships between physical activity and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 854.

Carson, V., Tremblay, M. S., & Chastin, S. (2017e). Cross-sectional associations between sleep duration, sedentary time, physical activity and adiposity indicators among canadian preschool children using compositional analyses. *BMC Public Health, 17*(5), 848.

Case, R. (1985). *Intellectual development: birth to adulthood*: Academic Press.

Chaput, J.-P., Carson, V., Gray, C. E., & Tremblay, M. S. (2014). Importance of All Movement Behaviors in a 24 Hour Period for Overall Health. *International Journal of Environmental Research and Public Health, 11*(12), 12575-12581. doi:10.3390/ijerph111212575

Chaput, J.-P., Gray, C. E., Poitras, V. J., Carson, V., Gruber, R., Birken, C. S., . . . Tremblay, M. S. (2017b). Systematic review of the relationships between sleep duration and health indicators in the early years (0–4 years). *BMC Public Health, 17*(5), 855. doi:10.1186/s12889-017-4850-2

Cohen, J. (1977). CHAPTER 9 - F Tests of Variance Proportions in Multiple Regression/Correlation Analysis. In J. Cohen (Ed.), *Statistical Power Analysis for the Behavioral Sciences* (pp. 407-453): Academic Press.

Dumuid, D., Pedišić, Ž., Stanford, T. E., Martín-Fernández, J.-A., Hron, K., Maher, C. A., . . . Olds, T. (2019). The compositional isotemporal substitution model: A method for estimating changes in a health outcome for reallocation of time between sleep, physical activity and sedentary behaviour. *Statistical Methods in Medical Research, 28*(3), 846-857. doi:10.1177/0962280217737805

Griffiths, A., Toovey, R., Morgan, P. E., & Spittle, A. J. (2018). Psychometric properties of gross motor assessment tools for children: a systematic review. *BMJ Open, 8*(10), e021734. doi:10.1136/bmjopen-2018-021734

Hjorth, M. F., Chaput, J.-P., Damsgaard, C. T., Dalskov, S.-M., Michaelsen, K. F., Tetens, I., & SjÖDin, A. (2012). Measure of sleep and physical activity by a single accelerometer: Can a waist-worn ActiGraph adequately measure sleep in children? *Sleep and Biological Rhythms, 10*(4), 328-335. doi:10.1111/j.1479-8425.2012.00578.x

Howard, S. J., & Melhuish, E. (2017). An early years toolbox for assessing early executive function, language, self-regulation, and social development: Validity, reliability, and preliminary norms. *Journal of Psychoeducational Assessment, 35*(3), 255-275.

Howard, S. J., & Okely, A. D. (2015). Catching fish and avoiding sharks. *Journal of Psychoeducational Assessment, 33*(6), 585-596. doi:doi:10.1177/0734282914562933

Katzmarzyk, P. T., Barreira, T. V., Broyles, S. T., Champagne, C. M., Chaput, J. P., Fogelholm, M., . . . Church, T. S. (2015). Physical Activity, Sedentary Time, and Obesity in an International Sample of Children. *Medicine & Science in Sports & Exercise, 47*(10), 2062-2069. doi:10.1249/mss.0000000000000649

Kuzik, N., Poitras, V. J., Tremblay, M. S., Lee, E.-Y., Hunter, S., & Carson, V. (2017). Systematic review of the relationships between combinations of movement behaviours and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 849.

Leppänen, M. H., Nyström, C. D., Henriksson, P., Pomeroy, J., Ruiz, J., Ortega, F., . . . Löf, M. (2016). Physical activity intensity, sedentary behavior, body composition and physical fitness in 4-year-old children: Results from the MINISTOP trial. *International Journal of Obesity*.

Luo, Z. C., Albertsson-Wikland, K., & Karlberg, J. (1998b). Target height as predicted by parental heights in a population-based study. *Pediatric research, 44*(4), 563.

Migueles, J. H., Cadenas-Sanchez, C., Ekelund, U., Delisle Nyström, C., Mora-Gonzalez, J., Löf, M., . . . Ortega, F. B. (2017). Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations. *Sports Medicine, 47*(9), 1821-1845. doi:10.1007/s40279-017-0716-0

Morra, S. (1994). Issues in working memory measurement: Testing for M capacity. *International Journal of Behavioral Development, 17*(1), 143-159.

Pedišić, Ž., Dumuid, D., & Olds, T. (2017). Integrating sleep, sedentary behaviour, and physical activity research in the emerging field of time-use epidemiology: Definitions, concepts, statistical methods, theoretical framework, and future directions. *Kinesiology: International journal of fundamental and applied kinesiology, 49*(2), 10-11.

Poitras, V. J., Gray, C. E., Janssen, X., Aubert, S., Carson, V., Faulkner, G., . . . Tremblay, M. (2017). Systematic review of the relationships between sedentary behavior and health indicators in the early years (aged 0-4 years). *BMC Public Health, 17*(5), 868.

Taylor, R. W., Haszard, J. J., Meredith-Jones, K. A., Galland, B. C., Heath, A.-L. M., Lawrence, J., . . . Taylor, B. J. (2018). 24-h movement behaviors from infancy to preschool: cross-sectional and longitudinal relationships with body composition and bone health. *International Journal of Behavioral Nutrition and Physical Activity, 15*(1), 118.

Terwee, C. B., Mokkink, L. B., van Poppel, M. N. M., Chinapaw, M. J. M., van Mechelen, W., & de Vet, H. C. W. (2010). Qualitative Attributes and Measurement Properties of Physical Activity Questionnaires. *Sports Medicine, 40*(7), 525-537. doi:10.2165/11531370-000000000-00000

Tremblay, M. S., Aubert, S., Barnes, J. D., Saunders, T. J., Carson, V., Latimer-Cheung, A. E., . . . on behalf of, S. T. C. P. P. (2017a). Sedentary Behavior Research Network (SBRN) – Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 75. doi:10.1186/s12966-017-0525-8

Tremblay, M. S., Chaput, J.-P., Adamo, K. B., Aubert, S., Barnes, J. D., Choquette, L., . . . Carson, V. (2017c). Canadian 24-hour movement guidelines for the early years (0–4 years): An integration of physical activity, sedentary behaviour, and sleep. *BMC Public Health, 17*(5), 874.

Tudor-Locke, C., Barreira, T. V., Schuna, J. M., Jr., Mire, E. F., & Katzmarzyk, P. T. (2014). Fully automated waist-worn accelerometer algorithm for detecting children's sleep-period time separate from 24-h physical activity or sedentary behaviors. *Applied Physiology, Nutrition, and Metabolism, 39*(1), 53-57. doi:10.1139/apnm-2013-0173

Ulrich, D. (2000). Test of Gross Motor Development (TGMD-2). Austin, TX: PRO-ED: Inc.

Van den Boogaart, K. G., & Tolosana-Delgado, R. (2013). *Analyzing compositional data with R* (Vol. 122): Springer.

Wiebe, S. A., Sheffield, T. D., & Espy, K. A. (2012). Separating the fish from the sharks: A longitudinal study of preschool response inhibition. *Child Development, 83*(4), 1245-1261.

World Health Organization Multicentre Growth Reference Study Group. (2006). WHO Child Growth Standards based on length/height, weight and age. *Acta Paediatrica, 95*(S450), 76-85. doi:10.1111/j.1651-2227.2006.tb02378.x

4.7 Oversized Tables (4.6 & 4.7)

Table 4.6: Significant Substitution Models (30 Minutes)

Outcome	+ Stationary - LPA	+ Stationary - MVPA	+ Stationary - Sleep	+ LPA - Stationary	+ LPA - MVPA	+ MVPA - Stationary	+ MVPA - LPA	+ MVPA - Sleep	+ Sleep - Stationary	+ Sleep - MVPA
Physical Development										
Locomotor Skills	1.94 (0.26, 3.63)	NS	NS	-1.88 (-3.49, -0.26)	-3.82 (-6.93, -0.71)	NS	3.28 (0.58, 5.97)	2.12 (0.27, 3.98)	NS	-2.79 (-5.16, -0.42)
Object Motor Skills	NS	-3.67 (-5.35, -1.99)	NS	NS	-4.79 (-7.26, -2.32)	2.75 (1.47, 4.04)	3.99 (1.85, 6.14)	2.62 (1.15, 4.09)	NS	-3.54 (-5.43, -1.66)
Total Motor Skills	3.18 (0.65, 5.72)	-5.67 (-8.86, -2.49)	NS	-2.99 (-5.42, -0.57)	-8.62 (-13.30, -3.94)	4.03 (1.60, 6.46)	7.27 (3.20, 11.33)	4.74 (1.96, 7.53)	NS	-6.33 (-9.90, -2.76)
BMI z-scores	NS	-0.23 (-0.46, -0.01)	NS	NS	NS	0.19 (0.02, 0.36)	NS	NS	NS	NS
Cognitive Development										
Vocabulary	NS	NS	1.03 (0.18, 1.88)	-1.11 (-2.21, -0.01)	NS	NS	NS	NS	-1.08 (-1.95, -0.20)	NS
Social-Emotional Development										
Cognitive Self-Regulation	NS	NS	NS	NS	-0.25 (-0.49, -0.01)	NS	0.22 (0.01, 0.43)	NS	NS	NS
Internalizing	NS	NS⊕	NS	NS	NS	NS⊖	NS	NS⊖	NS	NS⊕
Sociability	NS	-0.21 (-0.39, -0.03)	NS	NS	-0.26 (-0.52, -0.00)	0.16 (0.02, 0.29)	NS⊕	0.16 (0.01, 0.31)	NS	-0.21 (-0.40, -0.02)

Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; NS= non-significant; ⊕ =Became positively associated when removing influential participants according to Cook's d values >4/n; ⊖=Became negatively associated when removing influential participants according to Cook's d values >4/n

Table 4.7: General Trends of Significant Relations

Domain	**Direction**	**LPA**		**MVPA**		**Sleep**		**Stationary**	
		Linear	Substitution	Linear	Substitution	Linear	Substitution	Linear	Substitution
Physical	Favourable	0	0	**3**	**8**	0	0	0 (+1)	3
	Unfavourable	2	5	0	1	0	3	0	2
	Null	**3**	**10**	2	6	**5**	**12**	**5**	**10**
Cognitive	Favourable	0	0	0	0	0	0	**2**	1
	Unfavourable	0	1	0	0	0	1	0	0
	Null	**3**	**9**	**3**	**9**	**3**	**8**	1	**8**
Social-Emotional	Favourable	0	0	1	3 (+1)	0	0 (+1)	0	0 (+1)
	Unfavourable	0	2	0 (+1)	0 (+2)	0	2	0	1
	Null	**7**	**19**	**6 (-1)**	**18 (-3)**	**7**	**16 (-1)**	**7**	**17 (-1)**

LPA= Light-intensity physical activity; MVPA=Moderate- to vigorous- intensity physical activity; Sleep=total sleep; Stationary= Stationary time; Numbers In parentheses’ indicate number and direction of significant associations that were altered when removing influential participants according to Cook’s d values >4/n; Bolded values indicate ≥50% associations were in that direction

5 Manuscript 3

Parent-Child Movement Behaviours and Bluetooth Proximity in Preschool-Aged Children

Nicholas Kuzik, Patti-Jean Naylor, John C. Spence, Valerie Carson

5.1 Abstract

The objective of this study was to examine the associations of parental movement behaviours and parent-child proximity with preschool-aged children's movement behaviours using Bluetooth-enabled ActiGraph accelerometers and compositional analyses. Parent-child (n=89) movement behaviours were categorized as sleep, stationary time, light-intensity physical activity (LPA), and moderate- to vigorous-intensity physical activity (MVPA). Parent-child proximity behaviours were categorized as: no proximity (NP) detected, proximity detected and parent-child engaged in the same movement behaviour (Co), and proximity detected but mismatching parent-child movement behaviours (Close). Lastly, proximity movement behaviours were categorized specific to children's movement behaviours (e.g., NP-MVPA, Co-MVPA, and Close-MVPA). Parent-child movement behaviours were not associated with one another, close proximity was positively associated with children's LPA, and NP-MVPA was positively associated with children's MVPA in compositional and non-compositional regression analyses. Future parent-child proximity movement behaviour research is needed using longitudinal and experimental study designs and measuring the whole family unit.

5.2 Introduction

Ideal patterns of movement behaviours (e.g., more sleep, less sedentary behaviour, and more physical activity) have demonstrated numerous health benefits to the development of preschool-aged children (3–5 years) (Carson et al., 2017c; Chaput et al., 2017b; Kuzik et al., 2017; Poitras et al., 2017). To support movement behaviours, 24-Hour Movement Guidelines specific to this age group have been developed in several countries, as well as by the World Health Organization (Tremblay, 2019). However, studies reporting adherence to 24-Hour Movement Behaviour Guidelines show estimates of meeting all recommendations range from 5-24% (Berglind et al., 2018; Carson et al., 2019; Chaput et al., 2017a; Cliff et al., 2017; De Craemer et al., 2018; Guan et al., 2020; Hinkley et al., 2020; Leppänen et al., 2019). Thus, efforts are needed to identify modifiable correlates to improve movement behaviours in preschool-aged children. For instance, the family and the home environment are thought to have the greatest influence on the movement behaviours of young children (ParticipACTION, 2018; Rhodes et al., 2020).

Parental behaviours can directly influence children's behaviours (Taylor et al., 1994), particularly for children who have limited autonomy from their parents, such as preschool-aged children (Vaughn et al., 2013). Parental modeling of physical activity and sedentary behaviour is thought to be one explanation for this association (Bandura, 1986; Davison et al., 2013; Taylor et al., 1994; Trost & Loprinzi, 2011; Webber & Loescher, 2013; Yao & Rhodes, 2015). Frequently, parental modeling is conceptualized as the association between children's and parental daily physical activity and sedentary behaviour durations (Davison et al., 2013; Trost & Loprinzi, 2011; Yao & Rhodes, 2015). However, some conceptualizations of parental modeling move beyond an overall duration of parent-child behaviours, and consider parent-child proximity as a correlate of children's behaviours (e.g., children viewing their parent performing a behaviour, or parent and child co-participating in a behaviour) (Davison et al., 2013; Gattshall et al., 2008; Østbye et al., 2013). Parent-child proximity is also studied as a correlate of children's sleep through co-sleep, or when both parent and child are sleeping in the same room or bed (Mileva-Seitz et al., 2017; Sadeh, Tikotzky, & Scher, 2010; Thoman, 2006). Research focusing on co-sleep as well as physical activity and sedentary behaviour co-participation have identified the need for an objective measure of concurrent parent-child proximity and movement behaviours to better understand the associations between parent-child proximity and children's movement behaviours (Carson et al., 2020; Davison et al., 2013; Mâsse & Watts, 2013; Mileva-Seitz et al., 2017; Rhodes & Quinlan, 2014; Trost & Loprinzi, 2011).

Using ActiGraph accelerometers, Kuzik and Carson (Kuzik & Carson, 2018) validated a Bluetooth feature as an estimate of presence or absence of close-proximity between a parent and a young child. Two studies have used this feature to examine parent-child proximity, or proximity behaviours, and light-intensity physical activity (LPA), moderate- to vigorous-intensity physical activity (MVPA), and total physical activity (TPA). One study, with 17 mothers and children aged 1-5 years, found children with more co-MVPA (i.e., parent-child in the same proximity and both engaged in MVPA) accumulated more no proximity (NP)-MVPA (i.e., MVPA done by the child outside of parent-child proximity) (Dlugonski, DuBose, & Rider, 2017). While the other study, with 34 mothers and children aged 2-3 years, found that children with ≥ 60 minutes/day total MVPA engaged in more co-TPA compared to those with <60min/day of total MVPA (McCullough, Duch, & Garber, 2018). However, neither study examined how proximity-based patterns of LPA, MVPA, or TPA accumulation are related to children's total LPA, MVPA, or TPA (e.g., is more co-LPA associated with more total LPA). Further, only physical activity was examined in both studies. Thus, future studies are needed that examine how proximity-based patterns of accumulation are related to the total duration of all movement behaviours.

To examine movement behaviours, methods that appropriately control for their proportional nature are needed. Specifically, the categorization of movement behaviours makes them mutually exclusive and exhaustive, or the duration of movement behaviours has a constant sum (values always add to make a whole) constraint (Dumuid et al., 2017; Pedišić et al., 2017). Data with a constant sum constraint are perfectly collinear since one part of the composition can perfectly predict the remaining parts (Aitchison, 1986). Compositional analyses are one method that can appropriately handle the codependent aspects of movement behaviours (Chaput et al., 2014; Dumuid et al., 2017; Pedišić et al., 2017). Thus, the objective of this study is to examine the associations of parental movement behaviours and parent-child proximity with preschool-aged children's movement behaviours using Bluetooth-enabled ActiGraph accelerometers and compositional analyses.

5.3 Methods

5.3.1 Participants

Participants were from the Parent-Child Movement Behaviours and Pre-School Children's Development study. Parents/guardians of children aged 3-5 years, whose primary language at home was English were recruited from Edmonton, Canada and surrounding areas. Recruitment occurred through a local division of Sportball, a program that aims to teach children fundamental sport skills through play. The lead investigator recruited parents in person during Sportball summer camps (60 participated of 102 approached), and at Sportball classes. Further, recruitment materials were distributed to parents via email and social media by the local

Sportball organization. Due to logistical constraints, participation rates from Sportball classes, social media posts, and emails were not tracked. The total number of parent-child dyads that agreed to participate was 131. When applicable, parents decided amongst themselves which parent would participate. In nine cases, multiple preschool-aged children from the same family participated, while all other families had one parent and one child participate. Data collection occurred from July to November 2018. Ethics approval was granted by the University of Alberta Research Ethics Board, and all parents/guardians provided written informed consent.

5.3.2 Movement behaviours

Parent-child movement behaviours were measured with ActiGraph WGT3X-BT accelerometers. Accelerometers were programmed to start recording at midnight with the Bluetooth proximity feature enabled and set to a measurement frequency of 30 Hz. The day before recording started, parents were provided with the accelerometers attached to elastic belts and instructed, for themselves and their child/children, to wear them on the right hip continuously (i.e., 24-hours) for 7 days except during water-based activities. In addition to study protocol instructions (verbal and written), parents were given a log-sheet to track sleep and accelerometer wear time. After the completion of accelerometer protocols, the lead investigator visited the homes of parent–child dyads or an alternative preferred location (n=2) to collect the study materials.

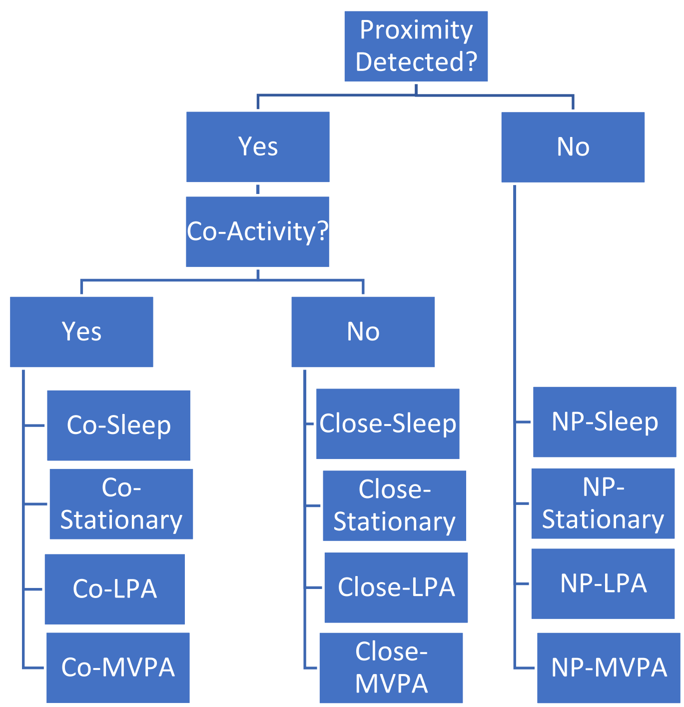
Low frequency extension (LFE) and normal filter files were downloaded from the accelerometers in 15-second epochs. Children's stationary time (i.e., waking behaviour devoid of ambulation regardless of posture (Tremblay et al., 2017a)) ≤25 counts/15 seconds), LPA (26-419 counts/15 seconds), and MVPA (≥420 counts/15 seconds) were categorized using normal filtered files. Total sleep was categorized using LFE files. Specifically, visual inspection guided by the log-sheet indicating sleep times and heuristics according to previous visual inspection methods were used to categorize daytime (e.g., nap) and nighttime sleep (Tudor-Locke et al., 2014). Sleep classifications were then merged with the other time-stamped movement behaviour classifications, and non-wear time was removed from waking movement behaviours (>20 minutes consecutive 0 counts, no interruptions). Lastly, data were removed that did not meet the valid days (i.e., ≥10 hours/day of waking day wear time) and valid participant data (i.e., ≥3 valid days) definitions (Cliff et al., 2009).

Normal filtered files were also used to classify parent's stationary time (0-24 counts/15-seconds), LPA (25-504 counts/15-seconds), and MVPA (≥505 counts/15-seconds) (Troiano et al., 2008). While LFE files were used to classify sleep using the Barreira modified Sadeh algorithm (Barreira et al., 2018). Sleep classifications were merged with normal filtered files and non-wear time was removed that was not sleep (≥60 minutes consecutive 0 counts, allowing for ≤2 minutes of consecutive counts between 0-100 (Troiano et al., 2008)).

5.3.3 __Proximity__

A Bluetooth proximity file detailing signal detection was also downloaded along with parent and child movement behaviour accelerometer files. Parent's accelerometers were set as beacons that emit Bluetooth signals continuously, while children's accelerometers were set as the receiver and recorded signal detection once every minute (ActiGraph Support Center, 2014). Bluetooth proximity values were dichotomized as *with*, signal detected, or a*way*, no signal detected, for every minute. According to a previous validation study, proximity values were smoothed to 5-minute overlapping windows, with the value being reclassified to *with* if any w*ith* signals were detected in the 5-minute window (Kuzik & Carson, 2018). Using parent-child proximity, children's proximity behaviours were created indicating the amount of time children were engaged in any movement behaviour with: no proximity (NP) detected, proximity detected and parent-child engaged in the same movement behaviour (Co), and proximity detected but mismatching parent-child movement behaviours (Close) (See Figure 5.1). For instance, the proximity behaviour Co would be the sum of time children spent in Co-Sleep, Co-Stationary, Co-LPA, and Co-MVPA. Further, children's proximity movement behaviours were created indicating the amount of time children spent in a specific movement behaviour for each proximity behaviour. For instance, children's MVPA would be categorized as NP-MVPA, Co-MVPA, and Close-MVPA.

Figure 5.1. Parent-child Bluetooth proximity variables



NP = No Proximity detected

5.3.4 Covariates

Covariates were selected based on previous development and movement behaviour literature (Carson et al., 2017a; Carson & Kuzik, 2017). Specifically, child-level (i.e., sex, age, ethnicity, hours of childcare attendance, and number of siblings), and parent- or household-level (i.e., age, education, income, relation to the child, marital status, size of yard, and type of home) covariates were measured in a demographic questionnaire or consent form completed by the parent. Response options for a number of covariates were collapsed due to frequency distributions. Child and parent age were calculated from birthdates and the date families received the accelerometer. Child race/ethnicity was classified as "Caucasian" or "non-Caucasian" from 12 response options. Number of siblings was classified as "0", "1", "≥2" total siblings, based on response options ranging from "0" to "≥3" for younger and older siblings. Hours/week of childcare attendance was calculated from the amount of time the child typically spent in care other than their parents. Parental relationship with the child was classified as "mother" or "father", since these were the only selected responses in this analytical sample. Parental education ranged from "University certificate, diploma, or degree above the bachelor's level" to "Less than high school diploma or its equivalent" and consisted of seven response options. Parental income ranged from "More than $200,000" to "Less than $25,000", decreasing by $25,000 at each response option, and included a "Do not know" option. One participant responded, "Do not know" and their response was imputed to the sample median. Marital status was classified as "married" or "not married" from 6 response options. Home type was classified as "one level" or "two levels" from nine response options. Yard size ranged from "A large yard (eg ¼ acre block or larger)" to "No yard at all" and consisted of five response options.

5.3.5 <u>Data analysis</u>

Standard descriptive statistics were calculated for all demographic variables. Compositional descriptive statistics were calculated for three time-use compositions: children's movement behaviours (i.e., the composition of time spent in sleep, stationary time, LPA, and MVPA), children's proximity behaviours (i.e., the composition of time spent in NP, Close, and Co), and proximity movement behaviours (e.g., the composition of time spent in NP-MVPA, Close-

MVPA, and Co-MVPA). The closed geometric mean of children's movement behaviours and children's proximity behaviours, normalized to 24-hours, were calculated as an indicator of centrality. Whereas, the closed geometric mean of children's proximity movement behaviours were left as a proportion since the sum of individual movement behaviours was not a fixed value. Variation matrixes were also calculated to present the proportionality between parts of a composition, with values closer to zero indicating a higher codependence.

Compositional data analyses were used to create regression models. Specifically, isometric log ratio transformations were calculated as pivot coordinates for each composition (i.e., parents movement behaviours, children's movement behaviours, proximity behaviours, and proximity movement behaviours) (Filzmoser et al., 2018). Zeroes were present for the variables Co-sleep and Close-sleep in one participant, so values were replaced with the smallest unit of measurement, since the presence of zeroes prevents log ratio transformations (Martín-Fernández, Barceló-Vidal, & Pawlowsky-Glahn, 2003). Isometric log ratio pivot coordinates are used to determine the strength and direction of association between one part of the composition (in relation to the rest of the composition) and an outcome or exposure variable of interest. Regression models with compositional outcome variables, as well as models with both outcome and exposure compositions, which rotate pivot coordinates for both compositions until all combinations are explored, were conducted (Filzmoser et al., 2018).

First, linear regression models were conducted between each potential covariate and pivot coordinates of children's movement behaviours. When a model was significant for a covariate and movement behaviour pivot coordinate, that covariate was added to subsequent models using that specific movement behaviour pivot coordinate. Second, linear regression models were conducted that used parental movement behaviour pivot coordinates as the exposure variables and the corresponding children's movement behaviour pivot coordinates as the outcome variables. The goal of these models was to examine the association between durations of a parent and child movement behaviour, relative to the rest of their movement behaviours (e.g., was a parent's MVPA, relative to the rest of their movement behaviours, related to their child's MVPA, relative to the rest of their movement behaviours). Third, linear regression models were then built with proximity behaviour pivot coordinates as the exposure variables and children's movement behaviour pivot coordinates as the outcome variables. The goal of these models was to examine the association between parent-child proximity behaviours, relative to the rest of the proximity behaviours, and children's movement behaviours, relative to the rest of their movement behaviours (e.g., was co-participation across all movement behaviours, relative to the rest of the proximity behaviours, associated with sleep duration, relative to the rest of the movement behaviours). The last set of linear regression models used the proximity movement behaviour (specific to the movement behaviour outcome) pivot coordinates as the exposure variables and children's movement behaviour pivot coordinates as the outcome variables. The goal of these models was to examine the association between children's proximity movement behaviours, relative to rest of the proximity movement behaviours specific to that movement behaviour outcome, and that specific movement behaviour, relative to the rest of the movement behaviours (e.g., was Co-MVPA, relative to Close-MVPA and NP-MVPA, associated with total MVPA, relative to the rest of the movement behaviour composition).

Finally, supplementary non-compositional linear regression analyses were conducted to facilitate comparison with previous studies. Children's movement behaviours were again considered the outcome variables in each regression model, but these variables and each exposure variable were considered in isolation. First, parental movement behaviours were considered the exposure variables (e.g., parental MVPA as exposure and children's MVPA as the outcome). Second, the duration of proximity behaviours were considered the exposure (e.g., NP as the exposure and children's sleep as the outcome). Lastly, proximity movement behaviours were calculated as a percent of that specific movement behaviour and considered exposure variables (e.g., Co-LPA/[Co-LPA + Close-LPA + NP-LPA] as the exposure variable and LPA as the outcome variable).

Additionally, sensitivity analyses were conducted for the main analyses and the supplementary analyses by removing all participants (n=19) from families (n=9) with more than one preschool aged child enrolled in the study and rerunning regression analyses to descriptively compare results. The Shapiro-Wilk test of normality and visual inspection of residuals (i.e., residuals vs fitted values, Q-Q, square root of Standardized residuals vs. fitted values, and Cook's Distance) were examined to ensure regression analysis assumptions were met. All data management and analyses were conducted in R (version 3.6.1, *"Action of the Toes"*) and statistical significance was set at $p < 0.05$.

5.4 <u>Results</u>

In total, 89 participants had usable dyadic data. From these data, children were an average age of 4.5 years and were predominantly boys (70%), while parents were an average age of 37.7 years and were mainly mothers (81.1%) (see Table 5.1). The closed geometric means for movement behaviours in a 24-hour period indicated children spent 11.0 hours sleeping, 6.1 hours stationary, 5.1 hours engaged in LPA, and 1.8 hours engaged in MVPA (see Table 5.2). Children spent the highest percentage of time outside of parent proximity (69.0%), and the time spent in parent proximity was similar in distribution for Co (16.2%) and Close (14.8%) (see Table 5.3).

Likewise, for proximity movement behaviours the highest percent of time was spent in NP for each movement behaviour (i.e., 90% NP-sleep, 58% NP-stationary, 58% NP-LPA, and 60% NP-MVPA) (see Figure 5.2). For the movement behaviour variation matrix values, stationary time and MVPA had the lowest codependence (0.15), while sleep and LPA had the highest codependence (0.02). Proximity behaviour variation matrix values generally indicated lower codependence (mean variance = 0.28) compared to the movement behaviour variation matrix (mean variance = 0.07).

Table 5.1: Demographic Characteristics

Demographic Variable	**Mean/Category (SD/Percent)**
Child Age (years)	4.55 (0.69)
Parent Age (years)	37.62 (5.13)
Childcare (hours/week)	22.07 (17.27)
Parent Education	Less than high school (1.12%)
	High school (4.49%)
	Trade certificate (1.12%)
	College certificate (7.87%)
	University certificate (2.25%)
	Bachelor's degree (49.44%)
	Above bachelor’s (33.71%)
Household Income	< \$25,000 (1.12%)
	\$25,000-\$50,000 (1.12%)
	\$50,001-\$75,000 (2.25%)
	\$75,001-\$100,000 (5.62%)
	\$100,001-\$125,000 (15.73%)
	\$125,001-\$150,000 (14.61%)
	\$150,010-\$175,000 (17.98%)
	\$175,001-\$200,000 (14.61%)

	> $200,000 (26.97%)
Home Type	One level (41.57%)
	Two levels (58.43%)
Yard Size	No yard (3.37%)
	No private yard (1.12%)
	Small yard (6.74%)
	Medium yard (68.54%)
	Large yard (20.22%)
Marital Status	Married (88.76%)
	Not married (11.23%)
Parent Relation to Child	Mother (82.02%)
	Father (17.98%)
Sex	Male (69.66%)
	Female (30.34%)
Siblings	None (16.85%)
	One (56.18%)
	Two or more (26.97%)
Ethnicity	Caucasian (71.91%)
	Non-Caucasian (28.09%)

Table 5.2: Children's Movement Behaviours Compositional Means and Variation Matrix

Movement Behaviours	**MVPA**	**LPA**	**Sleep**	**Stationary**
Mean	1.76	5.12	11.04	6.08
MVPA Variation	0.00			
LPA Variation	0.07	0.00		
Sleep Variation	0.09	0.02	0.00	
Stationary Variation	0.15	0.06	0.04	0.00

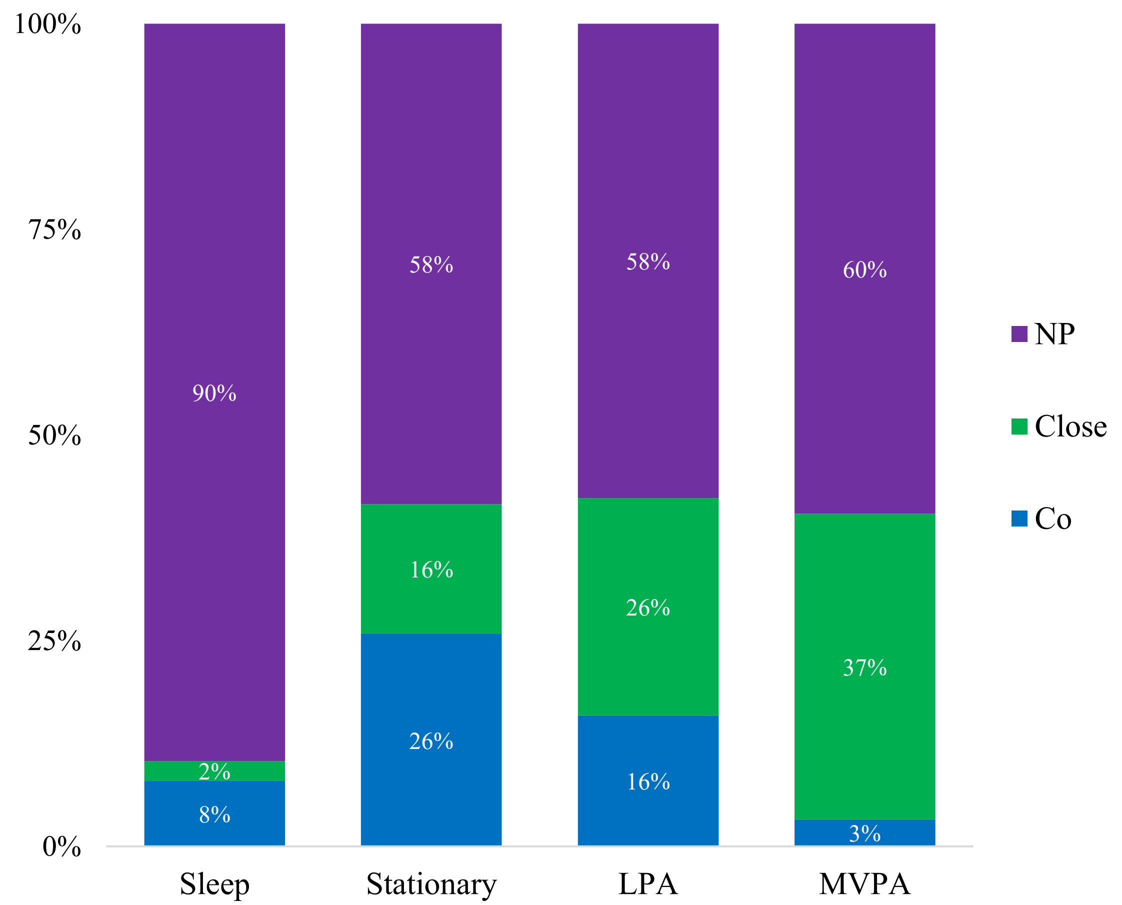
Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep.

Table 5.3: Children's Proximity Behaviours Compositional Means and Variation Matrix

Proximity	Co	Close	NP
Mean	3.89	3.55	16.56
Co Variation	0	0.10	0.48
Close Variation	0.10	0	0.26
NP Variation	0.48	0.26	0

Co=Co-proximity; Close=Close Proximity; NP=No Proximity.

Figure 5.2: Proximity Movement Behaviours



Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; Co=Co-proximity; Close=Close Proximity; NP=No Proximity.

Covariates that were significantly associated with a specific movement behaviour pivot coordinate and used to build subsequent regression models for at least one movement behaviour were: children's age, sex, ethnicity, number of siblings, time spent in childcare, as well as parental age, education, marital status, type of home, and size of yard (see Table 5.4). The pivot coordinate for sleep had the most significant covariates included in subsequent regression models with child age, ethnicity, and home type.

Table 5.4: Covariate and Movement Behaviour Bivariate Regression Models

Outcome	**Covariate**	**β (p-value)**
Sleep	Child Age (years)	-0.05 (0.00)
Sleep	Sex (Male, ref=female)	-0.05 (0.04)
Sleep	Home Type (Two levels, ref=one level)	-0.05 (0.03)
Stationary Time	Siblings (One, ref=none)	-0.17 (0.01)
Stationary Time	Siblings (Two or more, ref=none)	-0.14 (0.04)
Stationary Time	Yard Size (Continuous from smaller to larger yards)	0.07 (0.02)
LPA	Sex (Male, ref=female)	-0.06 (0.01)
LPA	Siblings (One, ref=none)	0.08 (0.01)
MVPA	Sex (Male, ref=female)	0.18 (0.00)
MVPA	Ethnicity (non-Caucasian, ref=Caucasian)	0.14 (0.02)

Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; ref=reference category.

Parental movement behaviours, relative to their movement behaviour composition, were not associated with children's movement behaviours, relative to their movement behaviour composition (Table 5.5). Further, no associations were found in sensitivity analyses that removed participants from families with more than one preschool aged child enrolled in the study. Lastly, findings were also non-significant in supplementary non-compositional analyses (Supplemental Table 5.1).

Table 5.5: Parent-Child Movement Behaviour Compositional Associations

Parent-Child Movement Behaviour	β (p-value)
Sleep	0.16 (0.21)
Stationary	0.06 (0.77)
LPA	0.10 (0.14)
MVPA	0.02 (0.74)

Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep.

Relative to the rest of the proximity behaviours, close proximity was positively associated and NP was negatively associated with Children's LPA, relative to the rest of their movement behaviours (Table 5.6). Within sensitivity analyses, relative to the rest of the proximity behaviours, Co proximity became positively associated and Close proximity became negatively associated with children's sleep, relative to the rest of the movement behaviours. In the supplementary analyses no significant associations were found for Co proximity and Close proximity with sleep, or for NP with LPA. However, the positive association between Close proximity and children's LPA was also found in the supplementary analyses. Specifically, each additional 10% of Close proximity was associated with 14 minutes/day more LPA (Supplemental Table 5.2).

Table 5.6: Proximity Behaviours and Children's Movement Behaviours Compositional Analyses

Children's Movement Behaviour	Proximity Behaviour	β (p-value)
Sleep	Close	-0.05 (0.42)⊖
	Co	0.05 (0.29)⊕
	NP	-0.00 (0.89)
Stationary	Close	-0.12 (0.26)
	Co	0.07 (0.46)
	NP	0.05 (0.26)
LPA	Close	**0.13 (0.03)**
	Co	-0.06 (0.22)
	NP	**-0.07 (0.01)**
MVPA	Close	-0.02 (0.89)
	Co	-0.04 (0.68)
	NP	0.06 (0.31)

Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; Co=Co-proximity; Close=Close Proximity; NP=No Proximity; Bolded values represent significant associations at $p<0.05$; ⊕ =Became significantly positively associated in sensitivity analyses; ⊖=Became significantly negatively associated in sensitivity analyses.

Lastly, for children's proximity movement behaviour analyses, NP-MVPA, relative to the rest of their proximity-MVPA composition, was positively associated with children's MVPA

(Table 5.7). This finding was consistent in sensitivity analyses. Further, supplementary analyses also found a positive association. Specifically, each additional 10% of NP-MVPA was associated with 5 minutes/day more MVPA (Supplemental Table 5.3).

Table 5.7: Children's Proximity Movement Behaviour Compositional Analyses

Children's movement Behaviour	Proximity Movement Behaviour	β (p-value)
Sleep	Close.Sleep	0.01 (0.27)
	Co.Sleep	-0.02 (0.07)
	NP.Sleep	0.01 (0.42)
Stationary	Close.Stationary	-0.00 (1.00)
	Co.Stationary	-0.02 (0.76)
	NP.Stationary	0.02 (0.59)
LPA	Close.LPA	0.03 (0.63)
	Co.LPA	0.01 (0.85)
	NP.LPA	-0.04 (0.12)
MVPA	Close.MVPA	-0.05 (0.43)
	Co.MVPA	-0.08 (0.09)
	NP.MVPA	**0.13 (0.01)**

Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; Co=Co-proximity; Close=Close Proximity; NP=No Proximity; Bolded values represent significant associations at p<0.05.

5.5 Discussion

The objective of this study was to examine the associations of parental movement behaviours, parent-child proximity behaviours, and proximity movement behaviours with children's movement behaviours using Bluetooth enabled ActiGraph accelerometers and compositional analyses. The use of the Bluetooth enabled accelerometers to measure parent-child proximity during children's movement behaviours addresses a major gap in the literature (Carson et al., 2020; Davison et al., 2013; Mâsse & Watts, 2013; Mileva-Seitz et al., 2017; Rhodes & Quinlan, 2014; Trost & Loprinzi, 2011). Notably there were no associations found between the total durations of parental and children's movement behaviours, but associations were found for parent-child proximity and children's LPA and MVPA. Findings for LPA and MVPA were consistent across compositional and non-compositional models as well as for sensitivity analyses.

No associations were found between the duration of parent-child physical activity in this study, which mirrored findings from a systematic review of correlates and determinants of physical activity in early years children (Bingham et al., 2016b). However, time spent in close proximity for parent-child dyads was associated with higher durations of children's total LPA. This could be similar to findings from the aforementioned systematic review showing that time spent playing with parents was positively associated with children's total physical activity (Bingham et al., 2016b). However, when looking at MVPA (a specific component of TPA) our study showed the more time children spent outside of parental proximity while engaged in MVPA was associated with higher total MVPA in children. Thus, our findings suggest time spent playing with a parent is not associated with children's MVPA. Discrepancies between the literature and the findings of this study may be a consequence of the use of an objective measure of parent-child proximity in this study compared to parent-reported estimates in previous work, or it could reflect a sampling bias due to the relatively small convenience sample, which had a high proportion of mother–son dyads. Future research should measure parent-child proximity movement behaviours in a larger more generalizable sample to better understand this association.

No significant associations were found between parent-child durations of stationary time or parent-child proximity and stationary time in this study. However, previous research has found positive associations between objectively measured total parental stationary time and children's stationary time (Carson et al., 2020; Hesketh et al., 2014; Hughes et al., 2016; Ruiz et al., 2011). Considering previous research has indicated more screen time and less physical activity equipment in the home are associated with preschool-aged children's stationary time (Byun et al., 2011), parental influence may rely more on their home environment rules and provisions for children's stationary time. Future research examining parent-child proximity and children's stationary time should also examine aspects of the home environment.

In this study co-sleeping was not associated with total sleep. Previous research with early years children has indicated that co-sleeping is associated with lower sleep compared to solitary sleep (Huang et al., 2016; Hysing et al., 2014; Mindell et al., 2013; Mindell et al., 2010; Touchette et al., 2009). Considering parental sleep duration and child sleep duration needs are vastly different, this could represent a downside to co-sleep as children regress towards parental sleep durations. Alternatively, since these studies were parent-report measures, and parent-report sleep more accurately predicts time in bed not time sleeping (Dayyat et al., 2011), this may reflect parents that co-sleep have more accurate estimates of children's sleep patterns. The differences between our findings and the existing literature could indicate that directly measured, versus parent-report, co-sleeping is not associated with total sleep. Alternatively, previous research has suggested that bed-sharing is associated with lower durations of sleep compared to room-sharing (Li et al., 2008). Thus, our results may highlight the Bluetooth proximity feature's inability to distinguish between room-sharing and bed-sharing. Future research using this Bluetooth proximity feature would benefit from asking parents what their sleep arrangements are when sharing a room (e.g., separate bed vs shared bed).

Our findings should be interpreted with caution since most dyads did not compromise of the whole family unit. While children with more NP-MVPA had higher durations of MVPA, they could have been engaged in MVPA within the proximity of family members not participating in the study, but outside of the proximity of the participating parent. This is especially relevant when considering the sample was predominantly mother-son dyads. There is a stronger association between father-son physical activity compared to mother-son physical activity in older boys (Yao & Rhodes, 2015). However, previous research has indicated that the associations between parent-child accelerometer measured stationary time, LPA, and MVPA were not moderated by parent-child sex combinations (e.g., father-son, mother-daughter) (Carson et al., 2020). Thus, future studies should measure the whole family unit to more robustly examine the findings in the current study.

Beyond not measuring the whole family unit, other limitations for this study deserve consideration. Mainly, the study design used convenience sampling and cross-sectional measurement, and the sample size was also relatively small (n=89 dyads). These aspects decrease the generalizability, causative interpretations, and power of detecting significant associations for our results. Generalizability may especially be problematic considering the high proportion of mother-son dyads. However, there were also several strengths of the study including measuring movement behaviours and proximity with accelerometers, the use of analyses sensitive to the compositional nature of movement behaviours, and comparing compositional and non-compositional models. Non-compositional analyses retained meaningful units in the results (minutes/day of movement behaviours) and enabled comparison with previous research. However, it is important to point out that the non-compositional analyses did not control for all components in the composition, so the compositional analyses was the more appropriate approach.

In summary, this examination of the associations between Bluetooth measured parent-child proximity and accelerometer measured parent-child movement behaviours showed parent-child movement behaviours were not associated, but some associations existed between proximity and children's movement behaviours. While proximity and sleep as well as stationary time did not appear to be linked, close proximity was positively associated with children's LPA, and children's MVPA outside of parental proximity was positively associated with children's MVPA. Future research should examine the findings in this study with more robust study designs (i.e., random sampling, longitudinal, and larger sample size), measuring the whole family unit, and determining the types of physical activities children are engaged in both in and out parent-child proximity.

5.6 Supplemental Tables

Supplementary Table 5.1: Parent-Child Movement Behaviour Associations

Parent-Child Movement Behaviour	β (p-value)
Sleep	0.01 (0.92)
Stationary	0.07 (0.43)
LPA	0.03 (0.68)
MVPA	0.03 (0.88)

Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep.

Supplementary Table 5.2: Proximity Behaviours and Children's Movement Behaviours Analyses

Children's Movement Behaviour	**Proximity Behaviour**	**β (p-value)**
Sleep	Close	2.44 (0.74)
	Co	2.44 (0.60)
	NP	-1.43 (0.63)
Stationary	Close	-16.55 (0.10)
	Co	-6.98 (0.29)
	NP	5.79 (0.17)
LPA	Close	**13.94 (0.04)**
	Co	4.81 (0.28)
	NP	-4.36 (0.13)
MVPA	Close	-5.91 (0.31)
	Co	-3.55 (0.32)
	NP	2.49 (0.28)

Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; Co=Co-proximity; Close=Close Proximity; NP=No Proximity; Bolded values represent significant associations at $p<0.05$.

Supplementary Table 5.3: Children's Proximity Movement Behaviour Analyses

Children's movement Behaviour	**Proximity Movement Behaviour**	**β (p-value)**
Sleep	Close.Sleep	10.66 (0.21)
	Co.Sleep	-1.46 (0.59)
	NP.Sleep	0.26 (0.91)
Stationary	Close.Stationary	-8.29 (0.34)
	Co.Stationary	-6.11 (0.22)
	NP.Stationary	4.57 (0.21)
LPA	Close.LPA	1.25 (0.75)
	Co.LPA	-3.10 (0.58)
	NP.LPA	0.09 (0.97)

MVPA	Close.MVPA	**-5.17 (0.01)[NS]**
	Co.MVPA	**-23.81 (0.01)**
	NP.MVPA	**5.18 (0.01)**

Stationary= Stationary time; LPA= light-intensity physical activity; MVPA=moderate- to vigorous-intensity physical activity; Sleep=total sleep; Co=Co-proximity; Close=Close Proximity; NP=No Proximity; Bolded values represent significant associations at p<0.05; NS= Became non-significant in sensitivity analyses.

5.7 References

ActiGraph Support Center. (2014). What is proximity tagging and how does it work? Retrieved from https://actigraph.desk.com/customer/en/portal/articles/2515795-what-is-proximity-tagging-and-how-does-it-work-

Aitchison, J. (1986). *The statistical analysis of compositional data*: Chapman & Hall, Ltd.

Bandura, A. (1986). Social foundations of thought and action : A social cognitive theory. Englewood Cliffs, N.J.: Prentice-Hall.

Barreira, T. V., Redmond, J. G., Brutsaert, T. D., Schuna, J. M., Jr., Mire, E. F., Katzmarzyk, P. T., & Tudor-Locke, C. (2018). Can an automated sleep detection algorithm for waist-worn accelerometry replace sleep logs? *Applied Physiology, Nutrition, and Metabolism, 43*(10), 1027-1032. doi:10.1139/apnm-2017-0860

Berglind, D., Ljung, R., Tynelius, P., & Brooke, H. L. (2018). Cross-sectional and prospective associations of meeting 24-h movement guidelines with overweight and obesity in preschool children. *Pediatric Obesity, 13*(7), 442-449. doi:10.1111/ijpo.12265

Bingham, D. D., Costa, S., Hinkley, T., Shire, K. A., Clemes, S. A., & Barber, S. E. (2016b). Physical activity during the early years: A systematic review of correlates and determinants. *American Journal of Preventive Medicine, 51*(3), 384-402. doi:10.1016/j.amepre.2016.04.022

Byun, W., Dowda, M., & Pate, R. R. (2011). Correlates of Objectively Measured Sedentary Behavior in US Preschool Children. *Pediatrics, 128*(5), 937-945. doi:10.1542/peds.2011-0748

Carson, V., Ezeugwu, V. E., Tamana, S. K., Chikuma, J., Lefebvre, D. L., Azad, M. B., . . . Mandhane, P. J. (2019). Associations between meeting the Canadian 24-Hour Movement Guidelines for the Early Years and behavioral and emotional problems among 3-year-olds. *Journal of Science and Medicine in Sport, 22*(7), 797-802. doi:https://doi.org/10.1016/j.jsams.2019.01.003

Carson, V., Hesketh, K. D., Rhodes, R. E., Rinaldi, C., Rodgers, W., & Spence, J. C. (2017a). Psychometric Properties of a Parental Questionnaire for Assessing Correlates of Toddlers' Physical Activity and Sedentary Behavior. *Measurement in Physical Education and Exercise Science, 21*(4), 190-200. doi:10.1080/1091367X.2017.1322087

Carson, V., & Kuzik, N. (2017). Demographic correlates of screen time and objectively measured sedentary time and physical activity among toddlers: a cross-sectional study. *BMC Public Health, 17*(1), 187. doi:10.1186/s12889-017-4125-y

Carson, V., Langlois, K., & Colley, R. (2020). Associations between parent and child sedentary behaviour and physical activity in early childhood. *Health Rep, 31*(2), 3-10. doi:10.25318/82-003-x202000200001-eng

Carson, V., Lee, E., Hewitt, L., Jennings, C., Hunter, S., Kuzik, N., . . . Tremblay, M. (2017c). Systematic review of the relationships between physical activity and health indicators in the early years (aged 0 to 4 years). *BMC Public Health, 17*(5), 854.

Chaput, J.-P., Carson, V., Gray, C. E., & Tremblay, M. S. (2014). Importance of All Movement Behaviors in a 24 Hour Period for Overall Health. *International Journal of Environmental Research and Public Health, 11*(12), 12575-12581. doi:10.3390/ijerph111212575

Chaput, J.-P., Colley, R. C., Janssen, I., Carson, V., Roberts, K. C., Aubert, S., & Tremblay, M. (2017a). Proportion of preschool-aged children meeting the Canadian 24-Hour Movement Guidelines for the Early Years and associations with adiposity: Results from the Canadian Health Measures Survey. *BMC Public Health, 17*(5), 829.

Chaput, J.-P., Gray, C. E., Poitras, V. J., Carson, V., Gruber, R., Birken, C. S., . . . Tremblay, M. S. (2017b). Systematic review of the relationships between sleep duration and health indicators in the early years (0–4 years). *BMC Public Health, 17*(5), 855. doi:10.1186/s12889-017-4850-2

Cliff, D. P., McNeill, J., Vella, S. A., Howard, S. J., Santos, R., Batterham, M., . . . de Rosnay, M. (2017). Adherence to 24-Hour Movement Guidelines for the Early Years and associations with social-cognitive development among Australian preschool children. *BMC Public Health, 17*(5), 857. doi:10.1186/s12889-017-4858-7

Cliff, D. P., Reilly, J. J., & Okely, A. D. (2009). Methodological considerations in using accelerometers to assess habitual physical activity in children aged 0-5 years. *Journal of Science and Medicine in Sport, 12*(5), 557-567. doi:10.1016/j.jsams.2008.10.008

Davison, K. K., Mâsse, L. C., Timperio, A., Frenn, M. D., Saunders, J., Mendoza, J. A., . . . Trost, S. G. (2013). Physical activity parenting measurement and research: Challenges, explanations, and solutions. *Childhood Obesity, 9*(s1), S-103-S-109.

Dayyat, E. A., Spruyt, K., Molfese, D. L., & Gozal, D. (2011). Sleep estimates in children: Parental versus actigraphic assessments. *Nat Sci Sleep, 3*, 115-123. doi:10.2147/nss.s25676

De Craemer, M., McGregor, D., Androutsos, O., Manios, Y., & Cardon, G. (2018). Compliance with 24-h Movement Behaviour Guidelines among Belgian Pre-School Children: The ToyBox-Study. *International Journal of Environmental Research and Public Health, 15*(10). doi:10.3390/ijerph15102171

Dlugonski, D., DuBose, K. D., & Rider, P. (2017). Accelerometer-Measured Patterns of Shared Physical Activity Among Mother-Young Child Dyads. *Journal of Physical Activity and Health, 14*(10), 808-814. doi:10.1123/jpah.2017-0028

Dumuid, D., Stanford, T., Martin-Fernández, J., Pedišić, Ž., Maher, C., Lewis, L., . . . Olds, T. (2017). Compositional data analysis for physical activity, sedentary time and sleep research. *Statistical Methods in Medical Research, 0*(0), 0962280217710835. doi:10.1177/0962280217710835

Filzmoser, P., Hron, K., & Templ, M. (2018). Applied compositional data analysis (pp. 181-205). Switzerland: Springer Nature.

Gattshall, M. L., Shoup, J. A., Marshall, J. A., Crane, L. A., & Estabrooks, P. A. (2008). Validation of a survey instrument to assess home environments for physical activity and healthy eating in overweight children. *International Journal of Behavioral Nutrition and Physical Activity, 5*(1), 3. doi:10.1186/1479-5868-5-3

Guan, H., Zhang, Z., Wang, B., Okely, A. D., Tong, M., Wu, J., & Zhang, T. (2020). Proportion of kindergarten children meeting the WHO guidelines on physical activity, sedentary behaviour and sleep and associations with adiposity in urban Beijing. *BMC Pediatrics, 20*(1), 70. doi:10.1186/s12887-020-1969-6

Hesketh, K. R., Goodfellow, L., Ekelund, U., McMinn, A. M., Godfrey, K. M., Inskip, H. M., . . . van Sluijs, E. M. (2014). Activity levels in mothers and their preschool children. *Pediatrics, 133*(4), e973-980. doi:http://dx.doi.org/10.1542/peds.2013-3153

Hinkley, T., Timperio, A., Watson, A., Duckham, R. L., Okely, A. D., Cliff, D., . . . Hesketh, K. D. (2020). Prospective associations with physiological, psychosocial and educational outcomes of meeting Australian 24-Hour Movement Guidelines for the Early Years. *International Journal of Behavioral Nutrition and Physical Activity, 17*(1), 36. doi:10.1186/s12966-020-00935-6

Huang, X.-N., Wang, H.-S., Chang, J.-J., Wang, L.-H., Liu, X.-C., Jiang, J.-X., & An, L. (2016). Feeding methods, sleep arrangement, and infant sleep patterns: A chinese population-based study. *World Journal of Pediatrics, 12*(1), 66-75.

Hughes, A. R., Muggeridge, D. J., Gibson, A.-M., Johnstone, A., & Kirk, A. (2016). Objectively measured sedentary time in children and their parents. *Aims Public Health, 3*(4), 823-836.

Hysing, M., Harvey, A. G., Torgersen, L., Ystrom, E., Reichborn-Kjennerud, T., & Sivertsen, B. (2014). Trajectories and predictors of nocturnal awakenings and sleep duration in infants. *Journal of Developmental & Behavioral Pediatrics, 35*(5), 309-316.

Kuzik, N., & Carson, V. (2018). Accelerometer Bluetooth proximity validation in parents and early years children. *Measurement in Physical Education and Exercise Science, 22*(4), 287-293. doi:10.1080/1091367X.2018.1442335

Kuzik, N., Poitras, V. J., Tremblay, M. S., Lee, E.-Y., Hunter, S., & Carson, V. (2017). Systematic review of the relationships between combinations of movement behaviours and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 849.

Leppänen, M. H., Ray, C., Wennman, H., Alexandrou, C., Sääksjärvi, K., Koivusilta, L., . . . Roos, E. (2019). Compliance with the 24-h movement guidelines and the relationship with anthropometry in Finnish preschoolers: the DAGIS study. *BMC Public Health, 19*(1), 1618. doi:10.1186/s12889-019-7967-7

Li, S., Jin, X., Yan, C., Wu, S., Jiang, F., & Shen, X. (2008). Bed- and room-sharing in Chinese school-aged children: Prevalence and association with sleep behaviors. *Sleep Medicine, 9*(5), 555-563. doi:https://doi.org/10.1016/j.sleep.2007.07.008

Martín-Fernández, J. A., Barceló-Vidal, C., & Pawlowsky-Glahn, V. (2003). Dealing with Zeros and Missing Values in Compositional Data Sets Using Nonparametric Imputation. *Mathematical Geology, 35*(3), 253-278. doi:10.1023/A:1023866030544

Mâsse, L. C., & Watts, A. W. (2013). Stimulating innovations in the measurement of parenting constructs. *Childhood Obesity, 9*(Suppl 1), S-5-S-13. doi:10.1089/chi.2013.0041

McCullough, A. K., Duch, H., & Garber, C. E. (2018). Interactive Dyadic Physical Activity and Spatial Proximity Patterns in 2-Year-Olds and Their Parents. *Children (Basel), 5*(12). doi:10.3390/children5120167

Mileva-Seitz, V. R., Bakermans-Kranenburg, M. J., Battaini, C., & Luijk, M. P. C. M. (2017). Parent-child bed-sharing: The good, the bad, and the burden of evidence. *Sleep Medicine Reviews, 32*, 4-27. doi:http://dx.doi.org/10.1016/j.smrv.2016.03.003

Mindell, J. A., Sadeh, A., Kwon, R., & Goh, D. Y. (2013). Cross-cultural differences in the sleep of preschool children. *Sleep Medicine, 14*(12), 1283-1289. doi:10.1016/j.sleep.2013.09.002

Mindell, J. A., Sadeh, A., Wiegand, B., How, T. H., & Goh, D. Y. (2010). Cross-cultural differences in infant and toddler sleep. *Sleep Medicine, 11*(3), 274-280. doi:10.1016/j.sleep.2009.04.012

Østbye, T., Malhotra, R., Stroo, M., Lovelady, C., Brouwer, R., Zucker, N., & Fuemmeler, B. (2013). The effect of the home environment on physical activity and dietary intake in preschool children. *International Journal of Obesity, 37*(10), 1314-1321. doi:http://dx.doi.org/10.1038/ijo.2013.76

ParticipACTION. (2018). The Brain+ Body Equation: Canadian kids need active bodies to build their best brains. The 2018 ParticipACTION report card on physical activity for children and youth: ParticipACTION Toronto.

Pedišić, Ž., Dumuid, D., & Olds, T. (2017). Integrating sleep, sedentary behaviour, and physical activity research in the emerging field of time-use epidemiology: Definitions, concepts, statistical methods, theoretical framework, and future directions. *Kinesiology: International journal of fundamental and applied kinesiology, 49*(2), 10-11.

Poitras, V. J., Gray, C. E., Janssen, X., Aubert, S., Carson, V., Faulkner, G., . . . Tremblay, M. (2017). Systematic review of the relationships between sedentary behavior and health indicators in the early years (aged 0-4 years). *BMC Public Health, 17*(5), 868.

Rhodes, R. E., Guerrero, M. D., Vanderloo, L. M., Barbeau, K., Birken, C. S., Chaput, J.-P., . . . Mâsse, L. C. (2020). Development of a consensus statement on the role of the family in the physical activity, sedentary, and sleep behaviours of children and youth. *International Journal of Behavioral Nutrition and Physical Activity, 17*(1), 1-31.

Rhodes, R. E., & Quinlan, A. (2014). *The family as a context for physical activity promotion* (2 ed.). New York: Routledge.

Ruiz, R., Gesell, S. B., Buchowski, M. S., Lambert, W., & Barkin, S. L. (2011). The relationship between hispanic parents and their preschool-aged children's physical activity. *Pediatrics, 127*(5), 888-895. doi:10.1542/peds.2010-1712

Sadeh, A., Tikotzky, L., & Scher, A. (2010). Parenting and infant sleep. *Sleep Medicine Reviews, 14*(2), 89-96. doi:https://doi.org/10.1016/j.smrv.2009.05.003

Taylor, W. C., Baranowski, T., & Sallis, J. F. (1994). Family determinants of childhood physical activity: A social-cognitive model. In R. K. Dishman (Ed.), *Advances in Exercise Adherence* (pp. 319–342). Champaign, IL: Human Kinetics.

Thoman, E. B. (2006). Co-sleeping, an ancient practice: Issues of the past and present, and possibilities for the future. *Sleep Medicine Reviews, 10*(6), 407-417. doi:https://doi.org/10.1016/j.smrv.2005.12.001

Touchette, E., Côté, S., Petit, D., Liu, X., Boivin, M., Falissard, B., . . . Montplaisir, J. (2009). Short nighttime sleep-duration and hyperactivity trajectories in early childhood. *Pediatrics, 124*(5), e985-e993.

Tremblay, M. S. (2019). Introducing 24-Hour Movement Guidelines for the Early Years: A New Paradigm Gaining Momentum. *Journal of Physical Activity and Health, 1*(aop), 1-4.

Tremblay, M. S., Aubert, S., Barnes, J. D., Saunders, T. J., Carson, V., Latimer-Cheung, A. E., . . . on behalf of, S. T. C. P. P. (2017a). Sedentary Behavior Research Network (SBRN) – Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 75. doi:10.1186/s12966-017-0525-8

Troiano, R. P., Berrigan, D., Dodd, K. W., Masse, L. C., Tilert, T., & McDowell, M. (2008). Physical activity in the united states measured by accelerometer. *Medicine & Science in Sports & Exercise, 40*(1), 181-188. doi:10.1249/mss.0b013e31815a51b3

Trost, S. G., & Loprinzi, P. D. (2011). Parental influences on physical activity behavior in children and adolescents: A brief review. *American Journal of Lifestyle Medicine, 5*.

Tudor-Locke, C., Barreira, T. V., Schuna, J. M., Jr., Mire, E. F., & Katzmarzyk, P. T. (2014). Fully automated waist-worn accelerometer algorithm for detecting children's sleep-period time separate from 24-h physical activity or sedentary behaviors. *Applied Physiology, Nutrition, and Metabolism, 39*(1), 53-57. doi:10.1139/apnm-2013-0173

Vaughn, A., Hales, D., & Ward, D. S. (2013). Measuring the physical activity practices used by parents of preschool children. *Medicine & Science in Sports & Exercise, 45*(12), 2369.

Webber, K. J., & Loescher, L. J. (2013). A systematic review of parent role modeling of healthy eating and physical activity for their young african-american children. *Journal for Specialists in Pediatric Nursing, 18*.

Yao, C. A., & Rhodes, R. E. (2015). Parental correlates in child and adolescent physical activity: A meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity, 12*(1), 1-38. doi:10.1186/s12966-015-0163-y

6 General Discussion

6.1 Overview

The overall goal of this dissertation was to systematically advance the field of movement behaviours in preschool-aged children using novel measurement and data analyses techniques. The integration of all movement behaviours in preschool-aged children is a broad and novel topic, so the VIRTUE framework was used to help systematically guide the research in this dissertation (Pedišić, Dumuid, & S Olds, 2017). Specific objectives of this dissertation fit within several research categories of the VIRTUE framework including, movement behaviour: 1) methods (in particular measurement), 2) relationships with health or development related outcomes, 3) prevalences, and 4) relationships with correlates. To address the overall goal and specific objectives, data were collected from one sample of parents and preschool-aged children. This chapter will summarize key findings from three manuscripts completed for this dissertation, outline overarching strengths and limitations of the research, as well as provide key implications for future research. When applicable the VIRTUE framework will also be used to organize discussion points in this chapter.

6.2 Summary of Key Findings

Measurement of movement behaviours is the first step in advancing this area of research, since without measurement movement behaviours could not be sufficiently studied (Pedišić et al., 2017). Measurement tools should ideally be valid and reliable estimations of the movement behaviours of interest and should be feasible within the study design selected (Pedišić et al., 2017). Findings from the literature review indicated the ActiGraph WGT3X-BT worn on the right hip was the ideal field-based measurement tool of movement behaviours in preschool-aged children. While previous studies have created techniques specific to the ActiGraph to classify physical activity and stationary time in preschool-aged children, no techniques existed for sleep classification (Migueles et al., 2017). Thus, the objective of Manuscript 1 was to create a technique to classify daytime and nighttime sleep. A ground truth estimate of sleep was measured through visual inspection, guided by previously published heuristics and parental sleep logs. Using raw accelerometer data 144 features were generated, and machine learning and simplified techniques predicted sleep using these features with almost perfect agreement to ground truth estimates of daytime and nighttime sleep. Though when comparing predicted participant-level daily summaries of sleep variables with ground truth summaries, significant differences were found for machine learning predictions, while non-significant differences were found for simplified techniques.

Health outcomes in movement behaviour research should follow the World Health Organization's definition of complete physical, mental, and social well-being, not simply the absence or presence of disease (Pedišić et al., 2017; World Health Organization, 1948). Further, compositional data analyses have been recommended to examine the associations between movement behaviour compositions and a breadth of biologically, psychologically, and socially relevant health or developmental indicators (Pedišić et al., 2017). Based on a systematic review I led, a lack of studies examining all movement behaviours and a range of development indicators in preschool-aged children was identified as a major gap in the literature (Kuzik et al., 2017). Additionally, only two studies were found after this review using compositional analyses, of which both examined physical development (Carson et al., 2017d; Taylor et al., 2018). Thus, the objective of Manuscript 2 was to examine the relationships between the composition of movement behaviours and a wide array of physical, cognitive, and social-emotional developmental indicators. Findings from this manuscript mainly confirmed the importance of moderate- to vigorous-intensity physical activity (MVPA), relative to the rest of the movement behaviour composition, for physical development. However, mixed findings between stationary time, relative to the rest of the movement behaviour composition, and cognitive development were also found.

Measuring the prevalence of movement behaviours in a sample of the population is important to determine if public health initiatives and interventions are needed that attempt to alter current prevalences towards a hypothetical optimum level (Pedišić et al., 2017). However, the prevalence of movement behaviours was not a primary objective of any manuscript in this dissertation but was still presented descriptively for all manuscripts. Manuscript 2 had the largest sample size (n=95) and on average children met the Canadian 24-Hour Movement Guidelines for the Early Years recommendations for sleep (sample:11.1 hours/day, guideline recommendation:10-13 hours/day) and physical activity (sample: 6.8 hours/day total physical activity [TPA], 1.8 hours/day MVPA; guideline recommendations: ≥3 hours/day TPA, ≥1 hour/day MVPA), and spent 6.1 hours/day in stationary time. Within Manuscript 1 (n=89), according to ground truth estimates children accumulated an average 10.8 hours of total sleep, 10.5 hours of nighttime sleep, and 0.3 hours of daytime sleep, again on average meeting the sleep recommendation from the Canadian 24-Hour Movement Guidelines for the Early Years.

Identifying correlates of movement behaviours generates potential targets for future interventions, as well identifying high-risk groups with sub-optimal movement behaviour compositions is important for targeted interventions (Pedišić et al., 2017). Within the literature review, parental movement behaviours and parent-child proximity behaviours were identified as potential modifiable correlates of preschool-aged children's movement behaviours. A previous validation study I led determined the ActiGraph WGT3X-BT accelerometer's Bluetooth feature was able to accurately estimate when parents and children were in close proximity, while simultaneously measuring parent-child movement behaviours (Kuzik & Carson, 2018). Thus, the objective of Manuscript 3 was to use compositional analyses to examine the associations of parental movement behaviours, parent-child proximity behaviours, and proximity movement behaviours with children's movement behaviours using Bluetooth enabled ActiGraph accelerometers. Findings from Manuscript 3 indicated that being in close proximity was positively associated with children's light-intensity physical activity (LPA), while time spent in no proximity (NP)-MVPA was positively associated with children's MVPA.

6.3 Strengths and limitations

The specific strengths of each manuscript are discussed in detail in Chapters 3-5. However, some overlap was seen across the studies. A major strength of the dissertation was the application of novel measurement and analyses. Specifically, raw accelerometer data processing and machine learning analyses were applied to children's data in Manuscript 1. Compositional analyses were used in Manuscripts 2 and 3, building on previous research primarily using non-compositional analyses. Further, the previously validated Bluetooth proximity feature was applied to a sample of parents and children wearing accelerometers to add context to movement behaviour data based on parent-child proximity behaviours. Another strength was the amount and variety of data collected. While only one sample of parents and children were used for these manuscripts, data was available for: 1 billion accelerometer observations used to generate raw data features;

physical, cognitive, and social-emotional development indicators; and parent-child movement behaviours and proximity behaviours.

The specific limitations of each manuscript are discussed in detail in Chapters 3-5. However, some overlap was seen across the studies. A major limitation of the dissertation was the data was collected from a relatively small (n=89-95 analytical sample sizes) convenience sample, using a cross-sectional study design. A small sample size reduced the ability to detect small, and in some models medium, effects. A convenience sample reduced the generalizability of findings to the broader population. As well, the cross-sectional study design prevented an understanding of the causal mechanisms for the findings. To confirm findings presented in this dissertation, data would need to be collected from a larger sample that is more representative of the broader population, using longitudinal or experimental study designs. Another common limitation was the measurement tools. While the use of accelerometers allowed for reliable, valid, and feasible measurement of motion based movement behaviours, some contextual information was missing that could have further explained the findings. For instance, using stationary time prevented knowing if this time was accumulated in potentially favourable (e.g., reading) or unfavourable (e.g., screen time) behaviours. Further, our co-sleep variable did not distinguish between sharing a bed or sharing a bedroom, which could be essential to determine if co-sleeping is beneficial or detrimental to sleep duration. Lastly, polysomnography could have provided a more valid ground truth measurement of sleep, compared to visual inspection of accelerometer data.

6.4 Implications and future directions

The main implication in this dissertation for future movement behaviour research in the methods category is that the presented techniques can be applied to accurately classify daytime and nighttime sleep in preschoolers wearing ActiGraph WGT3X-BT accelerometers. However, future validation research is still needed in larger more generalizable samples using ground truth measurements of sleep other than visual inspection (e.g., polysomnography, wearable cameras) to determine the robustness of these techniques. Further, the accuracy of sleep classification in this manuscript was higher than the best practice ActiGraph cut-points for stationary time and moderate- to vigorous-intensity physical activity in this age group (Janssen et al., 2013). Thus, using similar classification techniques, wearable cameras could also be used as a ground truth measure of physical activity, sedentary behaviour, and sleep in conjunction with ActiGraph accelerometers to create more accurate estimates of all movement behaviours. However, the use of wearable cameras would need to be studied for feasibility, due to potential ethical and compliance (e.g., discomfort wearing during sleep) issues.

Another implication for future movement behaviour research in the methods category was seen in Manuscripts 2 and 3, with the use of compositional analyses. The favourable associations for MVPA, relative to the rest of the movement behaviour composition, with aspects of physical development was in agreement with previous non-compositional research (Carson et al., 2017b). Additionally, within Manuscript 3 consistent results were found when comparing results from compositional and non-compositional analyses. The consistency of findings from compositional and non-compositional models speaks to the robustness of findings, in that whether the analysis controls for all movement behaviours or not, the association is present. Alternatively, some may argue based on this evidence, compositional analyses are not needed.

However, compositional analyses is the preferred method as it is able to sufficiently control for all the movement behaviours in a composition without introducing multicollinearity or spurious correlations (Aitchison, 1986; Dumuid et al., 2017).

The main implication for movement behaviour research in the health or development indicator category was that when controlling for all movement behaviours, MVPA is favourable for gross motor skills. Another implication was that stationary time, relative to the rest of the composition of movement behaviours, may be favourable for cognitive development. However, stationary time findings were mixed. Considering the heterogeneity in results, future research is needed that measures sedentary behaviour contexts. For instance, findings from a previous systematic review indicated cognitive development was favourably associated with parents reading with their children, while unfavourably associated with screen time (Poitras et al., 2017). Therefore, mixed results for stationary time could indicate children were engaging in more stationary time that was beneficial for cognitive development (e.g., reading) as opposed to stationary time that was unfavourable for cognitive development (e.g., screen time). Further, improvements in cognitive development have been observed in a standing desk intervention for school-aged children (Mehta, Shortz, & Benden, 2016). So, the inability to distinguish between sedentary (e.g., sitting) and non-sedentary (e.g., standing) postures could also be responsible for our mixed findings. Thus, future research should examine the association between sedentary behaviour and cognitive development, instead of measuring stationary time (i.e., motionless regardless of posture). For instance, measurement of posture (e.g., inclincometer) and sedentary behaviour context (e.g., time-use diary, wearable camera) could help identify if some sedentary behaviour patterns are favourable for cognitive development.

The main implications for movement behaviour research in the correlates category was parent-child proximity behaviours and proximity movement behaviours were correlates of children's movement behaviours, while parental movement behaviours were not a correlate of children's movement behaviours. Together, these findings could indicate that parent's can positively influence their children's physical activity by accumulating more time in close proximity, but having children accumulate MVPA outside of parental proximity. While the idea of promoting MVPA outside of parent proximity may be promising based on these results, a previous systematic review found parental time spent playing with children was positively associated with children's TPA (Bingham et al., 2016b). Thus, a more nuanced approach could be the scaffolding strategy influenced by Vygotsky's research (Vygotsky, 1980). That being adults should interact with children based on the needs of the individual child and situation, and if children are able to play independently in a meaningful way parental interaction is not needed (Trawick-Smith & Dziurgot, 2011). Thus, future research could create an intervention that teaches parents or early childhood educators how to observe children to determine how and when to interact with a child based on their individual need at that moment (Trawick-Smith & Dziurgot, 2011). However, a key limitation in this manuscript was the whole family unit was not measured. For instance, without measuring the whole family unit, it would be impossible to know if a child engaged in NP-MVPA in our analysis was actually engaged in co-MVPA with an unmeasured family member. Thus, to better understand these findings future studies are needed that measure the whole family unit.

Efforts were made to advance the research area of movement behaviours in preschool-aged children. Within the VIRTUE framework, research should progress towards the ultimate goal of creating interventions aimed at improving the movement behaviour compositions of preschool-aged children. Based on the findings presented in this dissertation, an intervention that measured all 24-hour movement behaviours and attempted to increase MVPA by increasing the time children spent in NP-MVPA, could be beneficial. However, recommending an intervention would be short-sighted based on the study design limitations described earlier, as well as the novelty of these findings. A better suggestion would be to design a longitudinal or experimental study, in a larger more generalizable sample, examining preschool-aged children's development and proximity movement behaviours in relation to the whole family unit.

6.5 Conclusion

For measurement of movement behaviours, with the addition of the sleep classification findings in Manuscript 1, techniques now exist to accurately classify all movement behaviours in preschool-aged children wearing ActiGraph accelerometers. Future studies should examine the robustness of this sleep classification technique with larger, more generalizable samples, and other forms of ground truth sleep measurement (e.g., polysomnography, wearable cameras). For relationships between movement behaviours and developmental indicators, findings presented from compositional analyses in Manuscript 2 supported previous non-compositional evidence of a favourable association between MVPA and physical development. Additionally, the associations between stationary time and cognitive development were mixed, so future research should examine sedentary behaviours (e.g., sitting, reading) and cognitive development to explain this heterogeneity. For relationships between correlates and movement behaviours, findings presented in Manuscript 3 did not support parental movement behaviours as modifiable correlates of children's movement behaviours, but associations were found for parent-child proximity behaviours and proximity movement behaviours. However, future research should measure the whole family unit to better understand the dynamics of the household that are associated with children's movement behaviours. Overall, to continue progressing the area of movement behaviours in preschool-aged children, future longitudinal and experimental research is needed with larger and more generalizable samples.

6.6 References

Aitchison, J. (1986). *The statistical analysis of compositional data*: Chapman & Hall, Ltd.

Bingham, D. D., Costa, S., Hinkley, T., Shire, K. A., Clemes, S. A., & Barber, S. E. (2016b). Physical activity during the early years: A systematic review of correlates and determinants. *American Journal of Preventive Medicine, 51*(3), 384-402. doi:10.1016/j.amepre.2016.04.022

Carson, V., Lee, E.-Y., Hewitt, L., Jennings, C., Hunter, S., Kuzik, N., . . . Tremblay, M. S. (2017b). Systematic review of the relationships between physical activity and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 854.

Carson, V., Tremblay, M., & Chastin, S. (2017d). Cross-sectional associations between sleep duration, sedentary time, physical activity and adiposity indicators among canadian preschool children using compositional analyses. *BMC Public Health, 17*(5), 848.

Dumuid, D., Stanford, T., Martin-Fernández, J., Pedišić, Ž., Maher, C., Lewis, L., . . . Olds, T. (2017). Compositional data analysis for physical activity, sedentary time and sleep research. *Statistical Methods in Medical Research, 0*(0), 0962280217710835. doi:10.1177/0962280217710835

Kuzik, N., & Carson, V. (2018). Accelerometer Bluetooth proximity validation in parents and early years children. *Measurement in Physical Education and Exercise Science, 22*(4), 287-293. doi:10.1080/1091367X.2018.1442335

Kuzik, N., Poitras, V. J., Tremblay, M. S., Lee, E.-Y., Hunter, S., & Carson, V. (2017). Systematic review of the relationships between combinations of movement behaviours and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 849.

Mehta, R. K., Shortz, A. E., & Benden, M. E. (2016). Standing up for learning: A pilot investigation on the neurocognitive benefits of stand-biased school desks. *International Journal of Environmental Research and Public Health, 13*(1), 59.

Migueles, J. H., Cadenas-Sanchez, C., Ekelund, U., Delisle Nyström, C., Mora-Gonzalez, J., Löf, M., . . . Ortega, F. B. (2017). Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations. *Sports Medicine, 47*(9), 1821-1845. doi:10.1007/s40279-017-0716-0

Pedišić, Ž., Dumuid, D., & Olds, T. (2017). Integrating sleep, sedentary behaviour, and physical activity research in the emerging field of time-use epidemiology: Definitions, concepts, statistical methods, theoretical framework, and future directions. *Kinesiology: International journal of fundamental and applied kinesiology, 49*(2), 10-11.

Taylor, R. W., Haszard, J. J., Meredith-Jones, K. A., Galland, B. C., Heath, A.-L. M., Lawrence, J., . . . Taylor, B. J. (2018). 24-h movement behaviors from infancy to preschool: cross-sectional and longitudinal relationships with body composition and bone health. *International Journal of Behavioral Nutrition and Physical Activity, 15*(1), 118.

Trawick-Smith, J., & Dziurgot, T. (2011). 'Good-fit' teacher–child play interactions and the subsequent autonomous play of preschool children. *Early Childhood Research Quarterly, 26*(1), 110-123. doi:https://doi.org/10.1016/j.ecresq.2010.04.005

Vygotsky, L. S. (1980). *Mind in society: The development of higher psychological processes*: Harvard university press.

World Health Organization. (1948). *Constitution of the world health organization.* Geneva.

Complete list of works cited

Acebo, C., Sadeh, A., Seifer, R., Tzischinsky, O., Wolfson, A. R., Hafer, A., & Carskadon, M. A. (1999). Estimating sleep patterns with activity monitoring in children and adolescents: How many nights are necessary for reliable measures? *Sleep, 22*(1), 95-103.

ActiGraph Corp. (2017). ActiGraph white paper: Estimating Human Position with the ActiGraph GT3X Triaxial Activity Monitor. Retrieved from http://actigraphcorp.com/wp-content/uploads/2015/06/Inclination-White-Paper.pdf

ActiGraph Support Center. (2014). What is proximity tagging and how does it work? Retrieved from https://actigraph.desk.com/customer/en/portal/articles/2515795-what-is-proximity-tagging-and-how-does-it-work-

ActiGraph Support Center. (2016). Lux measurements. Retrieved from https://actigraph.desk.com/customer/en/portal/articles/2515504-lux-measurements

ActiGraph Support Center. (2017a). ActiGraph white paper. Estimating human position with the ActiGraph GT3X triaxial activity monitor. Retrieved from http://actigraphcorp.com/wp-content/uploads/2015/06/Inclination-White-Paper.pdf

ActiGraph Support Center. (2017b). Where can I find documentation for the Sadeh and Cole-Kripke algorithms? Retrieved from https://actigraph.desk.com/customer/en/portal/articles/2515585-where-can-i-find-documentation-for-the-sadeh-and-cole-kripke-algorithms-

Addy, C. L., Trilk, J. L., Dowda, M., Byun, W., & Pate, R. R. (2014). Assessing preschool children's physical activity: How many days of accelerometry measurement. *Pediatric Exercise Science, 26*(1), 103-109. doi:10.1123/pes.2013-0021

Aitchison, J. (1986). *The statistical analysis of compositional data*: Chapman & Hall, Ltd.

Alhassan, S., Sirard, J. R., Kurdziel, L. B. F., Merrigan, S., Greever, C., & Spencer, R. M. C. (2017). Cross-Validation of Two Accelerometers for Assessment of Physical Activity and Sedentary Time in Preschool Children. *Pediatric Exercise Science, 29*(2), 268-277. doi:https://dx.doi.org/10.1123/pes.2016-0074

Babyak, M. A. (2004). What You See May Not Be What You Get: A Brief, Nontechnical Introduction to Overfitting in Regression-Type Models. *Psychosomatic Medicine, 66*(3), 411-421.

Bandura, A. (1986). Social foundations of thought and action : A social cognitive theory. Englewood Cliffs, N.J.: Prentice-Hall.

Barreira, T. V., Redmond, J. G., Brutsaert, T. D., Schuna, J. M., Jr., Mire, E. F., Katzmarzyk, P. T., & Tudor-Locke, C. (2018). Can an automated sleep detection algorithm for waist-worn accelerometry replace sleep logs? *Applied Physiology, Nutrition, and Metabolism, 43*(10), 1027-1032. doi:10.1139/apnm-2017-0860

Barreira, T. V., Schuna, J. M., Mire, E. F., Katzmarzyk, P. T., Chaput, J. P., Leduc, G., & Tudor-Locke, C. (2015). Identifying children's nocturnal sleep using 24-h waist accelerometry. *Medicine & Science in Sports & Exercise, 47*(5), 937-943. doi:https://dx.doi.org/10.1249/MSS.0000000000000486

Batty, G. D., Shipley, M. J., Gunnell, D., Huxley, R., Kivimaki, M., Woodward, M., . . . Smith, G. D. (2009). Height, wealth, and health: An overview with new data from three longitudinal studies. *Economics & Human Biology, 7*(2), 137-152. doi:https://doi.org/10.1016/j.ehb.2009.06.004

Bauman, A. E., Reis, R. S., Sallis, J. F., Wells, J. C., Loos, R. J. F., & Martin, B. W. (2012). Correlates of physical activity: Why are some people physically active and others not? *The Lancet, 380*(9838), 258-271.

Bauman, A. E., Sallis, J. F., Dzewaltowski, D. A., & Owen, N. (2002). Toward a better understanding of the influences on physical activity: The role of determinants, correlates, causal variables, mediators, moderators, and confounders. *American Journal of Preventive Medicine, 23*(2, Supplement 1), 5-14. doi:https://doi.org/10.1016/S0749-3797(02)00469-5

Beets, M. W., Cardinal, B. J., & Alderman, B. L. (2010). Parental social support and the physical activity-related behaviors of youth: A review. *Health Education & Behavior, 37*(5), 621-644.

Belsley, D. A., Edwin Kuh, and Roy E. Welsch. (1980). Detecting Influential Observations and Outliers *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity* (pp. 6-84). New York: John Wiley.

Berglind, D., Ljung, R., Tynelius, P., & Brooke, H. L. (2018). Cross-sectional and prospective associations of meeting 24-h movement guidelines with overweight and obesity in preschool children. *Pediatric Obesity, 13*(7), 442-449. doi:10.1111/ijpo.12265

Berk, L. E. (2013). *Development through the lifespan* (6 ed.). Boston, MA: Pearson.

Biddle, S. J. H., Atkin, A. J., Cavill, N., & Foster, C. (2011). Correlates of physical activity in youth: A review of quantitative systematic reviews. *International Review of Sport and Exercise Psychology, 4*(1), 25-49.

Biddle, S. J. H., Whitehead, S. H., O'Donovan, T. M., & Nevill, M. E. (2005). Correlates of participation in physical activity for adolescent girls: A systematic review of recent literature. *Journal of Physical Activity and Health, 2*(4), 423-434.

Bingham, D. D., Costa, S., Clemes, S. A., Routen, A. C., Moore, H. J., & Barber, S. E. (2016a). Accelerometer data requirements for reliable estimation of habitual physical activity and sedentary time of children during the early years-a worked example following a stepped approach. *Journal of Sports Sciences, 34*(20), 2005-2010.

Bingham, D. D., Costa, S., Hinkley, T., Shire, K. A., Clemes, S. A., & Barber, S. E. (2016b). Physical activity during the early years: A systematic review of correlates and determinants. *American Journal of Preventive Medicine, 51*(3), 384-402. doi:10.1016/j.amepre.2016.04.022

Breiman, L. (2001). Random Forests. *Machine Learning, 45*(1), 5-32. doi:10.1023/A:1010933404324

Brønd, J. C., & Arvidsson, D. (2016). Sampling frequency affects the processing of ActiGraph raw acceleration data to activity counts. *Journal of Applied Physiology, 120*(3), 362-369. doi:10.1152/japplphysiol.00628.2015

Bronfenbrenner, U. (1979). *The ecology of human development*: Harvard university press.

Butte, N. F., Puyau, M. R., Wilson, T. A., Liu, Butte, Nancy, F., . . . Issa, F. (2016). Role of physical activity and sleep duration in growth and body composition of preschool-aged children. *Obesity, 24*(6), 1328.

Byun, W., Beets, M., & Pate, R. (2015). Sedentary behavior in preschoolers: How many days of accelerometer monitoring is needed? *International Journal of Environmental Research and Public Health, 12*(10), 13148.

Byun, W., Dowda, M., & Pate, R. R. (2011). Correlates of Objectively Measured Sedentary Behavior in US Preschool Children. *Pediatrics, 128*(5), 937-945. doi:10.1542/peds.2011-0748

Campbell, S. B. (1998). Developmental perspectives *Handbook of Child Psychopathology* (pp. 3-35): Springer.

Carskadon, M. A., & Dement, W. C. (2005). Normal human sleep: an overview. *Principles and practice of sleep medicine, 4*, 13-23.

Carson, V., Ezeugwu, V. E., Tamana, S. K., Chikuma, J., Lefebvre, D. L., Azad, M. B., . . . Mandhane, P. J. (2019). Associations between meeting the Canadian 24-Hour Movement Guidelines for the Early Years and behavioral and emotional problems among 3-year-olds. *Journal of Science and Medicine in Sport, 22*(7), 797-802. doi:https://doi.org/10.1016/j.jsams.2019.01.003

Carson, V., Hesketh, K. D., Rhodes, R. E., Rinaldi, C., Rodgers, W., & Spence, J. C. (2017a). Psychometric Properties of a Parental Questionnaire for Assessing Correlates of Toddlers' Physical Activity and Sedentary Behavior. *Measurement in Physical Education and Exercise Science, 21*(4), 190-200. doi:10.1080/1091367X.2017.1322087

Carson, V., Hunter, S., Kuzik, N., Gray, C. E., Poitras, V. J., Chaput, J.-P., . . . Connor Gorber, S. (2016). Systematic review of sedentary behaviour and health indicators in school-aged children and youth: An update. *Applied Physiology, Nutrition, and Metabolism, 41*(6), S240-S265.

Carson, V., & Kuzik, N. (2017). Demographic correlates of screen time and objectively measured sedentary time and physical activity among toddlers: a cross-sectional study. *BMC Public Health, 17*(1), 187. doi:10.1186/s12889-017-4125-y

Carson, V., Langlois, K., & Colley, R. (2020). Associations between parent and child sedentary behaviour and physical activity in early childhood. *Health Rep, 31*(2), 3-10. doi:10.25318/82-003-x202000200001-eng

Carson, V., Lee, E.-Y., Hewitt, L., Jennings, C., Hunter, S., Kuzik, N., . . . Tremblay, M. S. (2017b). Systematic review of the relationships between physical activity and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 854.

Carson, V., Lee, E., Hewitt, L., Jennings, C., Hunter, S., Kuzik, N., . . . Tremblay, M. (2017c). Systematic review of the relationships between physical activity and health indicators in the early years (aged 0 to 4 years). *BMC Public Health, 17*(5), 854.

Carson, V., Tremblay, M., & Chastin, S. (2017d). Cross-sectional associations between sleep duration, sedentary time, physical activity and adiposity indicators among canadian preschool children using compositional analyses. *BMC Public Health, 17*(5), 848.

Carson, V., Tremblay, M. S., & Chastin, S. (2017e). Cross-sectional associations between sleep duration, sedentary time, physical activity and adiposity indicators among canadian preschool children using compositional analyses. *BMC Public Health, 17*(5), 848.

Carson, V., Tremblay, M. S., & Chastin, S. (2017f). Cross-sectional associations between sleep duration, sedentary time, physical activity, and adiposity indicators among Canadian preschool-aged children using compositional analyses. *BMC Public Health, 17*(5), 848. doi:10.1186/s12889-017-4852-0

Case, R. (1985). *Intellectual development: birth to adulthood*: Academic Press.

Caspersen, C. J., Powell, K. E., & Christenson, G. M. (1985). Physical activity, exercise, and physical fitness: Definitions and distinctions for health-related research. *Public Health Reports, 100*(2), 126.

Chaput, J.-P., Carson, V., Gray, C. E., & Tremblay, M. S. (2014). Importance of All Movement Behaviors in a 24 Hour Period for Overall Health. *International Journal of Environmental Research and Public Health, 11*(12), 12575-12581. doi:10.3390/ijerph111212575

Chaput, J.-P., Colley, R. C., Janssen, I., Carson, V., Roberts, K. C., Aubert, S., & Tremblay, M. (2017a). Proportion of preschool-aged children meeting the Canadian 24-Hour Movement Guidelines for the Early Years and associations with adiposity: Results from the Canadian Health Measures Survey. *BMC Public Health, 17*(5), 829.

Chaput, J.-P., Gray, C., Poitras, V., Carson, V., Gruber, R., Birken, C., . . . Tremblay, M. (2016). Systematic review of the relationships between sleep duration and health indicators in school-aged children and youth. *Applied Physiology, Nutrition, and Metabolism, 41*(6), S266-S282.

Chaput, J.-P., Gray, C. E., Poitras, V. J., Carson, V., Gruber, R., Birken, C. S., . . . Tremblay, M. S. (2017b). Systematic review of the relationships between sleep duration and health indicators in the early years (0–4 years). *BMC Public Health, 17*(5), 855. doi:10.1186/s12889-017-4850-2

Chaput, J. P., Gray, C., Poitras, V., Carson, V., Gruber, R., Birken, C., . . . Tremblay, M. (2017c). Systematic review of the relationships between sleep duration and health indicators in children aged 0-4 years. *BMC Public Health, 17*(5), 855.

Chastin, S. F., Palarea-Albaladejo, J., Dontje, M. L., & Skelton, D. A. (2015). Combined effects of time spent in physical activity, sedentary behaviors and sleep on obesity and cardio-metabolic health markers: A novel compositional data analysis approach. *PLOS ONE, 10*(10), e0139984. doi:10.1371/journal.pone.0139984

Chen, C., Liaw, A. & Breiman, L. . (2004). Using random forest to learn imbalanced data. *University of California, Berkeley*.

Cliff, D. P., McNeill, J., Vella, S. A., Howard, S. J., Santos, R., Batterham, M., . . . de Rosnay, M. (2017). Adherence to 24-Hour Movement Guidelines for the Early Years and associations with social-cognitive development among Australian preschool children. *BMC Public Health, 17*(5), 857. doi:10.1186/s12889-017-4858-7

Cliff, D. P., Reilly, J. J., & Okely, A. D. (2009). Methodological considerations in using accelerometers to assess habitual physical activity in children aged 0-5 years. *Journal of Science and Medicine in Sport, 12*(5), 557-567. doi:10.1016/j.jsams.2008.10.008

Cohen, J. (1977). CHAPTER 9 - F Tests of Variance Proportions in Multiple Regression/Correlation Analysis. In J. Cohen (Ed.), *Statistical Power Analysis for the Behavioral Sciences* (pp. 407-453): Academic Press.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. New York, NY.

Cohen, J., Onunaku, N., Clothier, S., & Poppe, J. (2005). *Helping young children succeed: Strategies to promote early childhood social and emotional development.* Paper presented at the Research and Policy Report. Washington, DC: National Conference of State Legislatures.

Cole, R. J., Kripke, D. F., Gruen, W., Mullaney, D. J., & Gillin, J. C. (1992). Automatic sleep/wake identification from wrist activity. *Sleep, 15*(5), 461-469. doi:10.1093/sleep/15.5.461

Cole, T. J., & Wright, C. M. (2011). A chart to predict adult height from a child's current height. *Annals of human biology, 38*(6), 662-668.

Colley, R. C., Harvey, A., Grattan, K. P., & Adamo, K. B. (2014). Impact of accelerometer epoch length on physical activity and sedentary behaviour outcomes for preschool-aged children. *Health Rep, 25*(1), 3.

Costa, S., Barber, S. E., Cameron, N., & Clemes, S. A. (2014). Calibration and validation of the ActiGraph GT3X+ in 2-3 year olds. *Journal of Science and Medicine in Sport, 17*(6), 617-622. doi:https://dx.doi.org/10.1016/j.jsams.2013.11.005

Cowan, N. (2008). What are the differences between long-term, short-term, and working memory? *Progress in brain research, 169*, 323-338. doi:10.1016/S0079-6123(07)00020-9

Craggs, C., Corder, K., Sluijs, E. M. F., & Griffin, S. J. (2011). Determinants of change in physical activity in children and adolescents: A systematic review. *American Journal of Preventive Medicine, 40*(6), 645-658.

Davison, K. K., Mâsse, L. C., Timperio, A., Frenn, M. D., Saunders, J., Mendoza, J. A., . . . Trost, S. G. (2013). Physical activity parenting measurement and research: Challenges, explanations, and solutions. *Childhood Obesity, 9*(s1), S-103-S-109.

Dayyat, E. A., Spruyt, K., Molfese, D. L., & Gozal, D. (2011). Sleep estimates in children: Parental versus actigraphic assessments. *Nat Sci Sleep, 3*, 115-123. doi:10.2147/nss.s25676

De Craemer, M., McGregor, D., Androutsos, O., Manios, Y., & Cardon, G. (2018). Compliance with 24-h Movement Behaviour Guidelines among Belgian Pre-School Children: The ToyBox-Study. *International Journal of Environmental Research and Public Health, 15*(10). doi:10.3390/ijerph15102171

Denham, S. A. (2006). Social-emotional competence as support for school readiness: What is it and how do we assess it? *Early Education and Development, 17*(1), 57-89.

Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*, 135-168.

Diamond, A. (2016). Why improving and assessing executive functions early in life is critical. *Executive Function in Preschool Age Children: Integrating Measurement, Neurodevelopment and Translational Research.* Washington, DC: American Psychological Association.

Dlugonski, D., DuBose, K. D., & Rider, P. (2017). Accelerometer-Measured Patterns of Shared Physical Activity Among Mother-Young Child Dyads. *Journal of Physical Activity and Health, 14*(10), 808-814. doi:10.1123/jpah.2017-0028

Doherty, A., Jackson, D., Hammerla, N., Plötz, T., Olivier, P., Granat, M. H., . . . Owen, C. G. (2017). Large scale population assessment of physical activity using wrist worn accelerometers: the UK biobank study. *PLOS ONE, 12*(2).

Dolinsky, D. H., Brouwer, R. J. N., Østbye, T., Evenson, K. R., & Siega-Riz, A. M. (2011). Peer reviewed: Correlates of sedentary time and physical activity among preschool-aged children. *Preventing Chronic Disease, 8*(6).

Downing, K. L., Hinkley, T., Salmon, J., Hnatiuk, J. A., & Hesketh, K. D. (2017). Do the correlates of screen time and sedentary time differ in preschool children? *BMC Public Health, 17*, 285. doi:10.1186/s12889-017-4195-x

Dubois, L., Ohm Kyvik, K., Girard, M., Tatone-Tokuda, F., Pérusse, D., Hjelmborg, J., . . . Martin, N. G. (2012). Genetic and environmental contributions to weight, height, and BMI from birth to 19 years of age: an international study of over 12,000 twin pairs. *PLOS ONE, 7*(2), e30153-e30153. doi:10.1371/journal.pone.0030153

Dumuid, D., Pedišić, Ž., Stanford, T. E., Martín-Fernández, J.-A., Hron, K., Maher, C. A., . . . Olds, T. (2019). The compositional isotemporal substitution model: A method for estimating changes in a health outcome for reallocation of time between sleep, physical activity and sedentary behaviour. *Statistical Methods in Medical Research, 28*(3), 846-857. doi:10.1177/0962280217737805

Dumuid, D., Stanford, T., Martin-Fernández, J., Pedišić, Ž., Maher, C., Lewis, L., . . . Olds, T. (2017). Compositional data analysis for physical activity, sedentary time and sleep research. *Statistical Methods in Medical Research, 0*(0), 0962280217710835. doi:10.1177/0962280217710835

Edwardson, C. L., & Gorely, T. (2010). Parental influences on different types and intensities of physical activity in youth: A systematic review. *Psychology of Sport and Exercise, 11*.

Edwardson, C. L., Rowlands, A. V., Bunnewell, S., Sanders, J., Esliger, D. W., Gorely, T., . . . Yates, T. (2016). Accuracy of posture allocation algorithms for thigh- and waist-worn accelerometers. *Medicine & Science in Sports & Exercise, 48*(6), 1085-1090. doi:10.1249/mss.0000000000000865

El-Sheikh, M., & Sadeh, A. (2015). Sleep and development: Introduction to the monograph. *Monographs of the Society for Research in Child Development, 80*(1), 1-14. doi:10.1111/mono.12141

Ellis, K., Kerr, J., Godbole, S., Staudenmayer, J., & Lanckriet, G. (2016). Hip and Wrist Accelerometer Algorithms for Free-Living Behavior Classification. *Medicine & Science in Sports & Exercise, 48*(5), 933-940. doi:10.1249/MSS.0000000000000840

Esliger, D., Copeland, J., Barnes, J., & Tremblay, M. (2005). Standardizing and optimizing the use of accelerometer data for free-living physical activity monitoring. *Journal of Physical Activity and Health, 2*(3), 366-383.

Evenson, K. R., Catellier, D. J., Gill, K., Ondrak, K. S., & McMurray, R. G. (2008). Calibration of two objective measures of physical activity for children. *Journal of Sports Sciences, 26*(14), 1557-1565.

Fabes, R. A., Gaertner, B. M., & Popp, T. K. (2006). Getting along with others: Social competence in early childhood. *Blackwell Handbook of Early Childhood Development*, 296-316.

Fenson, L., Dale, P. S., Reznick, J. S., Bates, E., Thal, D. J., Pethick, S. J., . . . Stiles, J. (1994). Variability in early communicative development. *Monographs of the Society for Research in Child Development, 59*(5), i-185. doi:10.2307/1166093

Filzmoser, P., Hron, K., & Templ, M. (2018). Applied compositional data analysis (pp. 181-205). Switzerland: Springer Nature.

Flynn, J. I., Coe, D. P., Larsen, C. A., Rider, B. C., Conger, S. A., & Bassett Jr, D. R. (2014). Detecting indoor and outdoor environments using the ActiGraph GT3X+ light sensor in children. *Medicine & Science in Sports & Exercise, 46*(1), 201-206.

Forney, G. D. (1973). The viterbi algorithm. *Proceedings of the Institute of Electrical and Electronics Engineers, 61*(3), 268-278.

Galland, B., Meredith-Jones, K., Terrill, P., & Taylor, R. (2014a). Challenges and emerging technologies within the field of pediatric actigraphy. *Frontiers in Psychiatry Frontiers Research Foundation, 5*, 99. doi:https://dx.doi.org/10.3389/fpsyt.2014.00099

Galland, B. C., Kennedy, G. J., Mitchell, E. A., & Taylor, B. J. (2012). Algorithms for using an activity-based accelerometer for identification of infant sleep-wake states during nap studies. *Sleep Medicine, 13*(6), 743-751. doi:10.1016/j.sleep.2012.01.018

Galland, B. C., Meredith-Jones, K., Gray, A., Sayers, R., Lawrence, J., Taylor, B., & Taylor, R. (2016). Criteria for nap identification in infants and young children using 24-h actigraphy and agreement with parental diary. *Sleep Medicine, 19*, 85-92. doi:https://dx.doi.org/10.1016/j.sleep.2015.10.013

Galland, B. C., Meredith-Jones, K., Terrill, P., & Taylor, R. (2014b). Challenges and Emerging Technologies within the Field of Pediatric Actigraphy. *Frontiers in Psychiatry, 5*(99). doi:10.3389/fpsyt.2014.00099

Garriguet, D., Colley, R., & Bushnik, T. (2017). Parent-Child association in physical activity and sedentary behaviour. *Health Rep, 28*(6), 3.

Gattshall, M. L., Shoup, J. A., Marshall, J. A., Crane, L. A., & Estabrooks, P. A. (2008). Validation of a survey instrument to assess home environments for physical activity and healthy eating in overweight children. *International Journal of Behavioral Nutrition and Physical Activity, 5*(1), 3. doi:10.1186/1479-5868-5-3

Geserick, M., Vogel, M., Gausche, R., Lipek, T., Spielau, U., Keller, E., . . . Körner, A. (2018). Acceleration of BMI in early childhood and risk of sustained obesity. *New England Journal of Medicine*.

Goldfield, G. S., Harvey, A., Grattan, K., & Adamo, K. B. (2012). Physical activity promotion in the preschool years: A critical period to intervene. *International Journal of Environmental Research and Public Health, 9*(4), 1326-1342. doi:10.3390/ijerph9041326

Gooch, D., Thompson, P., Nash, H. M., Snowling, M. J., & Hulme, C. (2016). The development of executive function and language skills in the early school years. *Journal of Child Psychology and Psychiatry, 57*(2), 180-187. doi:10.1111/jcpp.12458

Goodlin-Jones, B. L., Sitnick, S. L., Tang, K., Liu, J., & Anders, T. F. (2008). The children's sleep habits questionnaire in toddlers and preschool children. *Journal of Developmental and Behavioral Pediatrics, 29*(2), 82-88.

Griffiths, A., Toovey, R., Morgan, P. E., & Spittle, A. J. (2018). Psychometric properties of gross motor assessment tools for children: a systematic review. *BMJ Open, 8*(10), e021734. doi:10.1136/bmjopen-2018-021734

Guan, H., Zhang, Z., Wang, B., Okely, A. D., Tong, M., Wu, J., & Zhang, T. (2020). Proportion of kindergarten children meeting the WHO guidelines on physical activity, sedentary behaviour and sleep and associations with adiposity in urban Beijing. *BMC Pediatrics, 20*(1), 70. doi:10.1186/s12887-020-1969-6

Gustafson, S. L., & Rhodes, R. E. (2006). Parental correlates of physical activity in children and early adolescents. *Sports Medicine, 36*.

Halle, T. G., & Darling-Churchill, K. E. (2016). Review of measures of social and emotional development. *Journal of Applied Developmental Psychology, 45*(Supplement C), 8-18. doi:https://doi.org/10.1016/j.appdev.2016.02.003

Hardy Havens, D., & Zink, R. L. (1994). The "back to sleep" campaign. *Journal of Pediatric Health Care, 8*(5), 240-242. doi:http://dx.doi.org/10.1016/0891-5245(94)90070-1

Hesketh, K. R., Goodfellow, L., Ekelund, U., McMinn, A. M., Godfrey, K. M., Inskip, H. M., . . . van Sluijs, E. M. (2014). Activity levels in mothers and their preschool children. *Pediatrics, 133*(4), e973-980. doi:http://dx.doi.org/10.1542/peds.2013-3153

Hidding, L. M., Altenburg, T. M., Mokkink, L. B., Terwee, C. B., & Chinapaw, M. J. M. (2017). Systematic review of childhood sedentary behavior questionnaires: What do we know and what is next? *Sports Medicine, 47*(4), 677-699. doi:10.1007/s40279-016-0610-1

High, P. C. (2008). School Readiness. *Pediatrics, 121*(4), e1008-e1015. doi:10.1542/peds.2008-0079

Hinkley, T., O'connell, E., Okely, A. D., Crawford, D., Hesketh, K., & Salmon, J. (2012). Assessing volume of accelerometry data for reliability in preschool children. *Medicine & Science in Sports & Exercise, 44*(12), 2436-2441. doi:10.1249/MSS.0b013e3182661478

Hinkley, T., Timperio, A., Watson, A., Duckham, R. L., Okely, A. D., Cliff, D., . . . Hesketh, K. D. (2020). Prospective associations with physiological, psychosocial and educational outcomes of meeting Australian 24-Hour Movement Guidelines for the Early Years. *International Journal of Behavioral Nutrition and Physical Activity, 17*(1), 36. doi:10.1186/s12966-020-00935-6

Hislop, J., Law, J., Rush, R., Grainger, A., Bulley, C., Reilly, J. J., & Mercer, T. (2014). An investigation into the minimum accelerometry wear time for reliable estimates of habitual physical activity and definition of a standard measurement day in pre-school children. *Physiological Measurement, 35*(11), 2213.

Hjorth, M. F., Chaput, J.-P., Damsgaard, C. T., Dalskov, S.-M., Michaelsen, K. F., Tetens, I., & SjÖDin, A. (2012). Measure of sleep and physical activity by a single accelerometer: Can a waist-worn ActiGraph adequately measure sleep in children? *Sleep and Biological Rhythms, 10*(4), 328-335. doi:10.1111/j.1479-8425.2012.00578.x

Horst, K., Paw, M. J. C., Twisk, J. W. R., & Mechelen, W. (2007). A brief review on correlates of physical activity and sedentariness in youth. *Medicine & Science in Sports & Exercise, 39*(8), 1241-1250.

Howard, S. J., & Melhuish, E. (2017). An early years toolbox for assessing early executive function, language, self-regulation, and social development: Validity, reliability, and preliminary norms. *Journal of Psychoeducational Assessment, 35*(3), 255-275.

Howard, S. J., & Okely, A. D. (2015). Catching fish and avoiding sharks. *Journal of Psychoeducational Assessment, 33*(6), 585-596. doi:doi:10.1177/0734282914562933

Huang, X.-N., Wang, H.-S., Chang, J.-J., Wang, L.-H., Liu, X.-C., Jiang, J.-X., & An, L. (2016). Feeding methods, sleep arrangement, and infant sleep patterns: A chinese population-based study. *World Journal of Pediatrics, 12*(1), 66-75.

Hughes, A. R., Muggeridge, D. J., Gibson, A.-M., Johnstone, A., & Kirk, A. (2016). Objectively measured sedentary time in children and their parents. *Aims Public Health, 3*(4), 823-836.

Hysing, M., Harvey, A. G., Torgersen, L., Ystrom, E., Reichborn-Kjennerud, T., & Sivertsen, B. (2014). Trajectories and predictors of nocturnal awakenings and sleep duration in infants. *Journal of Developmental & Behavioral Pediatrics, 35*(5), 309-316.

Janssen, X., Cliff, D. P., Reilly, J. J., Hinkley, T., Jones, R. A., Batterham, M., . . . Okely, A. D. (2013). Predictive validity and classification accuracy of ActiGraph energy expenditure equations and cut-points in young children. *PLOS ONE, 8*(11), e79124. doi:10.1371/journal.pone.0079124

Johansson, E., Ekelund, U., Nero, H., Marcus, C., & Hagströmer, M. (2015). Calibration and cross-validation of a wrist-worn ActiGraph in young preschoolers. *Pediatric Obesity, 10*(1), 1-6. doi:10.1111/j.2047-6310.2013.00213.x

Johansson, E., Larisch, L. M., Marcus, C., & Hagstromer, M. (2016). Calibration and validation of a wrist- and hip-worn ActiGraph accelerometer in 4-year-old children. *PLOS ONE, 11*(9), e0162436. doi:https://dx.doi.org/10.1371/journal.pone.0162436

John, D., Miller, R., Kozey-Keadle, S., Caldwell, G., & Freedson, P. (2012). Biomechanical examination of the 'plateau phenomenon' in ActiGraph vertical activity counts. *Physiological Measurement, 33*(2), 219.

Jones, D. E., Greenberg, M., & Crowley, M. (2015). Early Social-Emotional Functioning and Public Health: The Relationship Between Kindergarten Social Competence and Future Wellness. *Am J Public Health, 105*(11), 2283-2290. doi:10.2105/ajph.2015.302630

Katzmarzyk, P. T., Barreira, T. V., Broyles, S. T., Champagne, C. M., Chaput, J. P., Fogelholm, M., . . . Church, T. S. (2015). Physical Activity, Sedentary Time, and Obesity in an International Sample of Children. *Medicine & Science in Sports & Exercise, 47*(10), 2062-2069. doi:10.1249/mss.0000000000000649

Kinder, J. R., Lee, K. A., Thompson, H., Hicks, K., Topp, K., & Madsen, K. A. (2012). Validation of a hip-worn accelerometer in measuring sleep time in children. *Journal of Pediatric Nursing, 27*(2), 127-133. doi:http://dx.doi.org/10.1016/j.pedn.2010.11.004

Klesges, R. C., Coates, T. J., Moldenhauer-Klesges, L. M., Holzer, B., Gustavson, J., & Barnes, J. (1984). The FATS: An observational system for assessing physical activity in children and associated parent behavior. *Behavioral Assessment, 6*(4), 333-345.

Kushida, C. A., Littner, M. R., Morgenthaler, T., Alessi, C. A., Bailey, D., Coleman, J., Jr., . . . Wise, M. (2005). Practice Parameters for the Indications for Polysomnography and Related Procedures: An Update for 2005. *Sleep, 28*(4), 499-523. doi:10.1093/sleep/28.4.499

Kuzik, N., & Carson, V. (2018). Accelerometer Bluetooth proximity validation in parents and early years children. *Measurement in Physical Education and Exercise Science, 22*(4), 287-293. doi:10.1080/1091367X.2018.1442335

Kuzik, N., Poitras, V. J., Tremblay, M. S., Lee, E.-Y., Hunter, S., & Carson, V. (2017). Systematic review of the relationships between combinations of movement behaviours and health indicators in the early years (0-4 years). *BMC Public Health, 17*(5), 849.

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *biometrics*, 159-174.

Lemoigne, Y. (2008). Molecular imaging computer reconstruction and practice. In A. Caner (Ed.). Dordrecht ;: Springer Science + Business Media B.V.

Leppänen, M. H., Nyström, C. D., Henriksson, P., Pomeroy, J., Ruiz, J., Ortega, F., . . . Löf, M. (2016). Physical activity intensity, sedentary behavior, body composition and physical fitness in 4-year-old children: Results from the MINISTOP trial. *International Journal of Obesity*.

Leppänen, M. H., Ray, C., Wennman, H., Alexandrou, C., Sääksjärvi, K., Koivusilta, L., . . . Roos, E. (2019). Compliance with the 24-h movement guidelines and the relationship with anthropometry in Finnish preschoolers: the DAGIS study. *BMC Public Health, 19*(1), 1618. doi:10.1186/s12889-019-7967-7

Li, S., Jin, X., Yan, C., Wu, S., Jiang, F., & Shen, X. (2008). Bed- and room-sharing in Chinese school-aged children: Prevalence and association with sleep behaviors. *Sleep Medicine, 9*(5), 555-563. doi:https://doi.org/10.1016/j.sleep.2007.07.008

Lubans, D. R., Morgan, P. J., Cliff, D. P., Barnett, L. M., & Okely, A. D. (2010). Fundamental movement skills in children and adolescents. *Sports Medicine, 40*(12), 1019-1035.

Luo, Z. C., Albertsson-Wikland, K., & Karlberg, J. (1998a). Target height as predicted by parental heights in a population-based study. *Pediatr Res, 44*(4), 563-571. doi:10.1203/00006450-199810000-00016

Luo, Z. C., Albertsson-Wikland, K., & Karlberg, J. (1998b). Target height as predicted by parental heights in a population-based study. *Pediatric research, 44*(4), 563.

Mannini, A., Intille, S. S., Rosenberger, M., Sabatini, A. M., & Haskell, W. (2013). Activity recognition using a single accelerometer placed at the wrist or ankle. *Medicine & Science in Sports & Exercise, 45*(11), 2193-2203. doi:10.1249/MSS.0b013e31829736d6

Martín-Fernández, J. A., Barceló-Vidal, C., & Pawlowsky-Glahn, V. (2003). Dealing with Zeros and Missing Values in Compositional Data Sets Using Nonparametric Imputation. *Mathematical Geology, 35*(3), 253-278. doi:10.1023/A:1023866030544

Mâsse, L. C., & Watts, A. W. (2013). Stimulating innovations in the measurement of parenting constructs. *Childhood Obesity, 9*(Suppl 1), S-5-S-13. doi:10.1089/chi.2013.0041

McAlister, D. (1879). The law of the geometric mean. *Proceedings of the royal society of london, 29*(196-199), 367-376.

McCullough, A. K., Duch, H., & Garber, C. E. (2018). Interactive Dyadic Physical Activity and Spatial Proximity Patterns in 2-Year-Olds and Their Parents. *Children (Basel), 5*(12). doi:10.3390/children5120167

Mehta, R. K., Shortz, A. E., & Benden, M. E. (2016). Standing up for learning: A pilot investigation on the neurocognitive benefits of stand-biased school desks. *International Journal of Environmental Research and Public Health, 13*(1), 59.

Meltzer, L. J., Montgomery-Downs, H. E., Insana, S. P., & Walsh, C. M. (2012). Use of actigraphy for assessment in pediatric sleep research. *Sleep Medicine Reviews, 16*(5), 463-475. doi:10.1016/j.smrv.2011.10.002

Mendonça, G., Cheng, L. A., Mélo, E. N., & Farias Júnior, J. C. (2014). Physical activity and social support in adolescents: A systematic review. *Health Education Research, 29*.

Meredith-Jones, K., Williams, S., Galland, B., Kennedy, G., & Taylor, R. (2016). 24 h accelerometry: Impact of sleep-screening methods on estimates of sedentary behaviour and physical activity while awake. *Journal of Sports Sciences, 34*(7), 679-685. doi:https://dx.doi.org/10.1080/02640414.2015.1068438

Migueles, J. H., Cadenas-Sanchez, C., Ekelund, U., Delisle Nyström, C., Mora-Gonzalez, J., Löf, M., . . . Ortega, F. B. (2017). Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations. *Sports Medicine, 47*(9), 1821-1845. doi:10.1007/s40279-017-0716-0

Migueles, J. H., Rowlands, A. V., Huber, F., Sabia, S., & van Hees, V. T. (2019). GGIR: A Research Community–Driven Open Source R Package for Generating Physical Activity and Sleep Outcomes From Multi-Day Raw Accelerometer Data. *Journal for the Measurement of Physical Behaviour, 2*(3), 188. doi:10.1123/jmpb.2018-0063

Mileva-Seitz, V. R., Bakermans-Kranenburg, M. J., Battaini, C., & Luijk, M. P. C. M. (2017). Parent-child bed-sharing: The good, the bad, and the burden of evidence. *Sleep Medicine Reviews, 32*, 4-27. doi:http://dx.doi.org/10.1016/j.smrv.2016.03.003

Mindell, J. A., Sadeh, A., Kwon, R., & Goh, D. Y. (2013). Cross-cultural differences in the sleep of preschool children. *Sleep Medicine, 14*(12), 1283-1289. doi:10.1016/j.sleep.2013.09.002

Mindell, J. A., Sadeh, A., Wiegand, B., How, T. H., & Goh, D. Y. (2010). Cross-cultural differences in infant and toddler sleep. *Sleep Medicine, 11*(3), 274-280. doi:10.1016/j.sleep.2009.04.012

Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., . . . Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety.

Proceedings of the National Academy of Sciences, 108(7), 2693-2698. doi:10.1073/pnas.1010076108

Morgan, P. L., Farkas, G., Hillemeier, M. M., Hammer, C. S., & Maczuga, S. (2015). 24-month-old children with larger oral vocabularies display greater academic and behavioral functioning at kindergarten entry. *Child Development, 86*(5), 1351-1370. doi:10.1111/cdev.12398

Morra, S. (1994). Issues in working memory measurement: Testing for M capacity. *International Journal of Behavioral Development, 17*(1), 143-159.

Must, A., & Strauss, R. S. (1999). Risks and consequences of childhood and adolescent obesity. *International Journal of Obesity, 23*(2), S2-S11. doi:10.1038/sj.ijo.0800852

Oftedal, S., Bell, K. L., Davies, P. S., Ware, R. S., & Boyd, R. N. (2014). Validation of accelerometer cut points in toddlers with and without cerebral palsy. *Medicine & Science in Sports & Exercise, 46*(9), 1808-1815. doi:https://dx.doi.org/10.1249/MSS.0000000000000299

Østbye, T., Malhotra, R., Stroo, M., Lovelady, C., Brouwer, R., Zucker, N., & Fuemmeler, B. (2013). The effect of the home environment on physical activity and dietary intake in preschool children. *International Journal of Obesity, 37*(10), 1314-1321. doi:http://dx.doi.org/10.1038/ijo.2013.76

Owen, N., Sugiyama, T., Eakin, E., Gardiner, P., Tremblay, M., & Sallis, J. (2011). Adults' sedentary behavior: Determinants and interventions. *American Journal of Preventive Medicine, 41*(2), 189-196.

ParticipACTION. (2018). The Brain+ Body Equation: Canadian kids need active bodies to build their best brains. The 2018 ParticipACTION report card on physical activity for children and youth: ParticipACTION Toronto.

Pate, R. R., Almeida, M. J., McIver, K. L., Pfeiffer, K. A., & Dowda, M. (2006). Validation and calibration of an accelerometer in preschool children. *Obesity, 14*(11), 2000-2006. doi:https://dx.doi.org/10.1038/oby.2006.234

Pawlowsky-Glahn, V., Egozcue, J. J., & Tolosana-Delgado, R. (2015). *Modeling and analysis of compositional data*: John Wiley & Sons.

Pearson, K. (1897). Mathematical contributions to the theory of evolution.—on a form of spurious correlation which may arise when indices are used in the measurement of organs. *Proceedings of the royal society of london, 60*(359-367), 489-498.

Pedišić, Ž. (2014). Measurement issues and poor adjustments for physical activity and sleep undermine sedentary behaviour research - the focus should shift to the balance between sleep, sedentary behaviour, standing and activity. *Kinesiology: International journal of fundamental and applied kinesiology, 46*(1), 135-146.

Pedišić, Ž., Dumuid, D., & Olds, T. (2017). Integrating sleep, sedentary behaviour, and physical activity research in the emerging field of time-use epidemiology: Definitions, concepts, statistical methods, theoretical framework, and future directions. *Kinesiology: International journal of fundamental and applied kinesiology, 49*(2), 10-11.

Piek, J. P., Dawson, L., Smith, L. M., & Gasson, N. (2008). The role of early fine and gross motor development on later motor and cognitive ability. *Human Movement Science, 27*(5), 668-681. doi:https://doi.org/10.1016/j.humov.2007.11.002

Poitras, V. J., Gray, C. E., Borghese, M. M., Carson, V., Chaput, J.-P., Janssen, I., . . . Kho, M. E. (2016). Systematic review of the relationships between objectively measured physical activity and health indicators in school-aged children and youth 1. *Applied Physiology, Nutrition, and Metabolism, 41*(6), S197-S239.

Poitras, V. J., Gray, C. E., Janssen, X., Aubert, S., Carson, V., Faulkner, G., . . . Tremblay, M. (2017). Systematic review of the relationships between sedentary behavior and health indicators in the early years (aged 0-4 years). *BMC Public Health, 17*(5), 868.

Pugliese, J., & Tinsley, B. (2007). Parental socialization of child and adolescent physical activity: A meta-analysis. *Journal of Family Psychology, 21*.

Puhl, J., Greaves, K., Hoyt, M., & Baranowski, T. (1990). Children's activity rating scale (cars): Description and calibration. *Research Quarterly for Exercise and Sport, 61*(1), 26-36. doi:10.1080/02701367.1990.10607475

Pulakka, A., Cheung, Y. B., Ashorn, U., Penpraze, V., Maleta, K., Phuka, J. C., & Ashorn, P. (2013). Feasibility and validity of the ActiGraph GT3X accelerometer in measuring physical activity of Malawian toddlers. *Acta Paediatrica, 102*(12), 1192-1198. doi:https://dx.doi.org/10.1111/apa.12412

Quante, M., Kaplan, E. R., Rueschman, M., Cailler, M., Buxton, O. M., & Redline, S. (2015). Practical considerations in using accelerometers to assess physical activity, sedentary behavior, and sleep. *Sleep Health: Journal of the National Sleep Foundation, 1*(4), 275-284. doi:10.1016/j.sleh.2015.09.002

Rhodes, R. E., Guerrero, M. D., Vanderloo, L. M., Barbeau, K., Birken, C. S., Chaput, J.-P., . . . Mâsse, L. C. (2020). Development of a consensus statement on the role of the family in the physical activity, sedentary, and sleep behaviours of children and youth. *International Journal of Behavioral Nutrition and Physical Activity, 17*(1), 1-31.

Rhodes, R. E., & Quinlan, A. (2014). *The family as a context for physical activity promotion* (2 ed.). New York: Routledge.

Robinson, L. E., Stodden, D. F., Barnett, L. M., Lopes, V. P., Logan, S. W., Rodrigues, L. P., & D'Hondt, E. (2015). Motor Competence and its Effect on Positive Developmental Trajectories of Health. *Sports Medicine, 45*(9), 1273-1284. doi:10.1007/s40279-015-0351-6

Rosenberger, M. E., Buman, M. P., Haskell, W. L., McConnell, M. V., & Carstensen, L. L. (2016). 24 hours of sleep, sedentary behavior, and physical activity with nine wearable devices. *Medicine & Science in Sports & Exercise, 48*(3), 457-465. doi:10.1249/MSS.0000000000000778

Ruiz, R., Gesell, S. B., Buchowski, M. S., Lambert, W., & Barkin, S. L. (2011). The relationship between hispanic parents and their preschool-aged children's physical activity. *Pediatrics, 127*(5), 888-895. doi:10.1542/peds.2010-1712

Saarni, C. (1999). *The development of emotional competence*: Guilford Press.

Sadeh, A. (2004). A brief screening questionnaire for infant sleep problems: Validation and findings for an internet sample. *Pediatrics, 113*(6), e570-e577. doi:10.1542/peds.113.6.e570

Sadeh, A. (2015). III. Sleep assessment methods. *Monographs of the Society for Research in Child Development, 80*(1), 33-48. doi:10.1111/mono.12143

Sadeh, A., Acebo, C., Seifer, R., Aytur, S., & Carskadon, M. A. (1995). Activity-based assessment of sleep-wake patterns during the 1st year of life. *Infant Behavior and Development, 18*(3), 329-337.

Sadeh, A., Alster, J., Urbach, D., & Lavie, P. (1989). Actigraphically based automatic bedtime sleep-wake scoring: validity and clinical applications. *Journal of ambulatory monitoring, 2*(3), 209-216.

Sadeh, A., Tikotzky, L., & Scher, A. (2010). Parenting and infant sleep. *Sleep Medicine Reviews, 14*(2), 89-96. doi:https://doi.org/10.1016/j.smrv.2009.05.003

Sallis, J. F., Owen, N., & Fisher, E. (2015). *Ecological models of health behavior* (5 ed.). San Francisco: Jossey-Bass.

Sallis, J. F., Owen, N., & Fotheringham, M. J. (2000). Behavioral epidemiology: a systematic framework to classify phases of research on health promotion and disease prevention. *Annals of Behavioral Medicine, 22*(4), 294-298.

Sallis, J. F., Prochaska, J. J., & Taylor, W. C. (2000). A review of correlates of physical activity of children and adolescents. *Medicine & Science in Sports & Exercise, 32*.

Salmon, J., Tremblay, M., Marshall, S., & Hume, C. (2011). Health risks, correlates, and interventions to reduce sedentary behavior in young people. *American Journal of Preventive Medicine, 41*(2), 197-206. doi:http://dx.doi.org/10.1016/j.amepre.2011.05.001

Sameroff, A. (1975). Transactional models in early social relations. *Human Development, 18*(1-2), 65-79.

Schmutz, E. A., Leeger-Aschmann, C. S., Radtke, T., Muff, S., Kakebeeke, T. H., Zysset, A. E., . . . Meyer, A. H. (2017). Correlates of preschool children's objectively measured physical activity and sedentary behavior: A cross-sectional analysis of the splashy study. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 1.

Scholle, S., Scholle, H. C., Kemper, A., Glaser, S., Rieger, B., Kemper, G., & Zwacka, G. (2003). First night effect in children and adolescents undergoing polysomnography for sleep-disordered breathing. *Clinical Neurophysiology, 114*(11), 2138-2145. doi:https://doi.org/10.1016/S1388-2457(03)00209-8

Seale, J., & Rumpler, W. (1997). Comparison of energy expenditure measurements by diet records, energy intake balance, doubly labeled water and room calorimetry. *European Journal of Clinical Nutrition, 51*(12), 856-863.

Secker, D. (2010). Promoting optimal monitoring of child growth in Canada: using the new WHO growth charts. *Can J Diet Pract Res, 71*(1), e1-3. doi:10.3148/71.1.2010.54

Shaul, S., & Schwartz, M. (2014). The role of the executive functions in school readiness among preschool-age children. *Reading and Writing, 27*(4), 749-768. doi:10.1007/s11145-013-9470-3

Sirard, J. R., & Pate, R. R. (2001). Physical activity assessment in children and adolescents. *Sports Medicine, 31*(6), 439-454. doi:10.2165/00007256-200131060-00004

Sirard, J. R., Trost, S. G., Pfeiffer, K. A., Dowda, M., & Pate, R. R. (2005). Calibration and evaluation of an objective measure of physical activity in preschool children. *Journal of Physical Activity and Health, 2*(3), 345-357.

Sluijs, E. M. F., Kriemler, S., & McMinn, A. M. (2011). The effect of community and family interventions on young people's physical activity levels: A review of reviews and updated systematic review. *British Journal of Sports Medicine, 45*.

Sluijs, E. M. F., McMinn, A. M., & Griffin, S. J. (2007). Effectiveness of interventions to promote physical activity in children and adolescents: Systematic review of controlled trials. *Bmj, 335*.

Smith, C., Galland, B., Taylor, R., & Meredith-Jones, K. (2020). ActiGraph GT3X+ and Actical Wrist and Hip Worn Accelerometers for Sleep and Wake Indices in Young Children

Using an Automated Algorithm: Validation With Polysomnography. *Frontiers in Psychiatry, 10*, 958-958. doi:10.3389/fpsyt.2019.00958

Spence, J. C., & Lee, R. E. (2003). Toward a comprehensive model of physical activity. *Psychology of Sport and Exercise, 4*(1), 7-24. doi:http://dx.doi.org/10.1016/S1469-0292(02)00014-6

Sterdt, E., Liersch, S., & Walter, U. (2013). Correlates of physical activity of children and adolescents: A systematic review of reviews. *Health Education Journal, 73*.

Tandon, P. S., Saelens, B. E., Zhou, C., Kerr, J., & Christakis, D. A. (2013). Indoor versus outdoor time in preschoolers at child care. *American Journal of Preventive Medicine, 44*(1), 85-88. doi:https://doi.org/10.1016/j.amepre.2012.09.052

Taylor, R. W., Haszard, J. J., Meredith-Jones, K. A., Galland, B. C., Heath, A.-L. M., Lawrence, J., . . . Taylor, B. J. (2018). 24-h movement behaviors from infancy to preschool: cross-sectional and longitudinal relationships with body composition and bone health. *International Journal of Behavioral Nutrition and Physical Activity, 15*(1), 118.

Taylor, W. C., Baranowski, T., & Sallis, J. F. (1994). Family determinants of childhood physical activity: A social-cognitive model. In R. K. Dishman (Ed.), *Advances in Exercise Adherence* (pp. 319–342). Champaign, IL: Human Kinetics.

Terwee, C. B., Mokkink, L. B., van Poppel, M. N. M., Chinapaw, M. J. M., van Mechelen, W., & de Vet, H. C. W. (2010). Qualitative Attributes and Measurement Properties of Physical Activity Questionnaires. *Sports Medicine, 40*(7), 525-537. doi:10.2165/11531370-000000000-00000

Thoman, E. B. (1990). Sleeping and waking states in infants: A functional perspective. *Neuroscience & Biobehavioral Reviews, 14*(1), 93-107.

Thoman, E. B. (2006). Co-sleeping, an ancient practice: Issues of the past and present, and possibilities for the future. *Sleep Medicine Reviews, 10*(6), 407-417. doi:https://doi.org/10.1016/j.smrv.2005.12.001

Touchette, E., Côté, S., Petit, D., Liu, X., Boivin, M., Falissard, B., . . . Montplaisir, J. (2009). Short nighttime sleep-duration and hyperactivity trajectories in early childhood. *Pediatrics, 124*(5), e985-e993.

Trawick-Smith, J., & Dziurgot, T. (2011). 'Good-fit' teacher–child play interactions and the subsequent autonomous play of preschool children. *Early Childhood Research Quarterly, 26*(1), 110-123. doi:https://doi.org/10.1016/j.ecresq.2010.04.005

Tremblay, M. S. (2019). Introducing 24-Hour Movement Guidelines for the Early Years: A New Paradigm Gaining Momentum. *Journal of Physical Activity and Health, 1*(aop), 1-4.

Tremblay, M. S., Aubert, S., Barnes, J. D., Saunders, T. J., Carson, V., Latimer-Cheung, A. E., . . . on behalf of, S. T. C. P. P. (2017a). Sedentary Behavior Research Network (SBRN) – Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 75. doi:10.1186/s12966-017-0525-8

Tremblay, M. S., Chaput, J.-P., Adamo, K. B., Aubert, S., Barnes, J. D., Choquette, L., . . . Carson, V. (2017b). Canadian 24-hour movement guidelines for the early years (0-4 years): An integration of physical activity, sedentary behaviour, and sleep. *BMC Public Health, 17*(5), 874.

Tremblay, M. S., Chaput, J.-P., Adamo, K. B., Aubert, S., Barnes, J. D., Choquette, L., . . . Carson, V. (2017c). Canadian 24-hour movement guidelines for the early years (0–4 years): An integration of physical activity, sedentary behaviour, and sleep. *BMC Public Health, 17*(5), 874.

Troiano, R. P., Berrigan, D., Dodd, K. W., Masse, L. C., Tilert, T., & McDowell, M. (2008). Physical activity in the united states measured by accelerometer. *Medicine & Science in Sports & Exercise, 40*(1), 181-188. doi:10.1249/mss.0b013e31815a51b3

Trost, S. G. (2007). State of the art reviews: Measurement of physical activity in children and adolescents. *American Journal of Lifestyle Medicine, 1*(4), 299-314.

Trost, S. G., Fees, B. S., Haar, S. J., Murray, A. D., & Crowe, L. K. (2012). Identification and validity of accelerometer cut-points for toddlers. *Obesity, 20*(11), 2317-2319. doi:10.1038/oby.2011.364

Trost, S. G., & Loprinzi, P. D. (2011). Parental influences on physical activity behavior in children and adolescents: A brief review. *American Journal of Lifestyle Medicine, 5*.

Tudor-Locke, C., Barreira, T., Schuna, J., Mire, E., Chaput, J., Fogelholm, M., . . . Katzmarzyk, P. (2015). Improving wear time compliance with a 24-hour waist-worn accelerometer protocol in the international study of childhood obesity, lifestyle and the environment (iscole). *International Journal of Behavioral Nutrition and Physical Activity, 12*(1), 11. doi:10.1186/s12966-015-0172-x

Tudor-Locke, C., Barreira, T. V., Schuna, J. M., Jr., Mire, E. F., & Katzmarzyk, P. T. (2014). Fully automated waist-worn accelerometer algorithm for detecting children's sleep-period time separate from 24-h physical activity or sedentary behaviors. *Applied Physiology, Nutrition, and Metabolism, 39*(1), 53-57. doi:10.1139/apnm-2013-0173

Ulrich, D. (2000). Test of Gross Motor Development (TGMD-2). Austin, TX: PRO-ED: Inc.

Vaha-Ypya, H., Vasankari, T., Husu, P., Suni, J., & Sievanen, H. (2015). A universal, accurate intensity-based classification of different physical activities using raw data of accelerometer. *Clin Physiol Funct Imaging, 35*(1), 64-70. doi:10.1111/cpf.12127

Vale, S., Santos, R., Silva, P., Soares-Miranda, L., & Mota, J. (2009). Preschool children physical activity measurement: Importance of epoch length choice. *Pediatric Exercise Science, 21*(4), 413-420.

Van Cauwenberghe, E., Gubbels, J., De Bourdeaudhuij, I., & Cardon, G. (2011a). Feasibility and validity of accelerometer measurements to assess physical activity in toddlers. *International Journal of Behavioral Nutrition and Physical Activity, 8*(1), 67. doi:10.1186/1479-5868-8-67

Van Cauwenberghe, E., Labarque, V., Trost, S. G., Bourdeaudhuij, I., & Cardon, G. (2011b). Calibration and comparison of accelerometer cut points in preschool children. *Pediatric Obesity, 6*(2Part2).

Van den Boogaart, K. G., & Tolosana-Delgado, R. (2013). *Analyzing compositional data with R* (Vol. 122): Springer.

Vaughn, A., Hales, D., & Ward, D. S. (2013). Measuring the physical activity practices used by parents of preschool children. *Medicine & Science in Sports & Exercise, 45*(12), 2369.

Vygotsky, L. S. (1980). *Mind in society: The development of higher psychological processes*: Harvard university press.

Webber, K. J., & Loescher, L. J. (2013). A systematic review of parent role modeling of healthy eating and physical activity for their young african-american children. *Journal for Specialists in Pediatric Nursing, 18*.

Welk, G. J. (2002). *Physical activity assessments for health-related research*: Human Kinetics.

Welk, G. J., Wood, K., & Morss, G. (2003). Parental influences on physical activity in children: An exploration of potential mechanisms. *Pediatric Exercise Science, 15*(1), 19-33.

Wiebe, S. A., & Karbach, J. (2018). *Executive function : development across the life span*: New York : Routledge, Taylor & Francis Group, 2018.

Wiebe, S. A., Sheffield, T. D., & Espy, K. A. (2012). Separating the fish from the sharks: A longitudinal study of preschool response inhibition. *Child Development, 83*(4), 1245-1261.

Willetts, M., Hollowell, S., Aslett, L., Holmes, C., & Doherty, A. (2018). Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 UK Biobank participants. *Scientific Reports, 8*(1), 7961. doi:10.1038/s41598-018-26174-1

World Health Organization. (1948). *Constitution of the world health organization.* Geneva.

World Health Organization Multicentre Growth Reference Study Group. (2006). WHO Child Growth Standards based on length/height, weight and age. *Acta Paediatrica, 95*(S450), 76-85. doi:10.1111/j.1651-2227.2006.tb02378.x

Yao, C. A., & Rhodes, R. E. (2015). Parental correlates in child and adolescent physical activity: A meta-analysis. *International Journal of Behavioral Nutrition and Physical Activity, 12*(1), 1-38. doi:10.1186/s12966-015-0163-y

Zelazo, P. D., Anderson, J. E., Richler, J., Wallner-Allen, K., Beaumont, J. L., & Weintraub, S. (2013). II. NIH toolbox cognition battery (CB): Measuring executive function and attention. *Monographs of the Society for Research in Child Development, 78*(4), 16-33. doi:10.1111/mono.12032

Zhang, S., Rowlands, A. V., Murray, P., & Hurst, T. L. (2012). Physical Activity Classification Using the GENEA Wrist-Worn Accelerometer. *Medicine & Science in Sports & Exercise, 44*(4), 742-748. doi:10.1249/MSS.0b013e31823bf95c

Zhang, Z., Sousa-Sá, E., Pereira, J., Chaput, J.-P., Okely, A., Feng, X., & Santos, R. (2019). Correlates of nocturnal sleep duration, nocturnal sleep variability, and nocturnal sleep problems in toddlers: results from the GET UP! Study. *Sleep Medicine, 53*, 124-132. doi:10.1016/j.sleep.2018.08.035

Zucchini, W., MacDonald, I. L., & Langrock, R. (2017). *Hidden Markov models for time series: an introduction using R*: CRC press.